# Optimization of a QoS-Aware Channel Assignment for Cognitive Radio Networks

Hooman Razavi
Faculty of Electrical and Computer Engineering
K.N. Toosi University of Technology
Tehran, Iran
Email: hrazavi@ee.kntu.ac.ir

Abdorasoul Ghasemi
Faculty of Electrical and Computer Engineering
K.N. Toosi University of Technology
Tehran, Iran
Email: arghasemi@kntu.ac.ir

*Abstract*—**The channel assignment problem is an important issue in cognitive radio networks because the conventional fixed spectrum allocation mechanism leads to significant spectrum underutilization. In this paper, the QoS-aware channel assignment is formulated as an optimization problem. The objective is to maximize the utilization of spectrum opportunities and fairness among secondary users (SUs) subject to constraints of different SUs demands, spectrum levels of the QoS and channel availabilities for each SU. Designing the QoS-Aware channel assignment scheme is based on genetic algorithm (GA) and quantum genetic algorithm (QGA). Two different objective functions are proposed as the network utilization and fairness indexes. Simulation results are provided to show the efficiency of the proposed method.**

***Keywords—Channel Assignment; Cognitive radio; Evolutionary Algorithms; Optimization; QoS-Aware;***

## I. INTRODUCTION

The use of wireless communications has increased rapidly during the past two decades, which has eventually increased the demand of bandwidth by transmitters and receivers in a communication network. For improving the utilization of the spectrum resources, cognitive radio paradigm has been proposed. In a cognitive radio network (CRN), the licensed primary users (PUs) and opportunistic SUs coexist in utilizing the spectrum [1]. In CRNs, PUs should be protected while SUs access the spectrum. In the spectrum overlay paradigm, SUs are only permitted to access spectrum channels which are not being used by PUs. In the spectrum underlay paradigm, it is required that an interference threshold be maintained at receiving points of the PUs [2].

One of the main topics in CRNs is dynamic spectrum management where efficient channel assignment mechanisms are the most important research issue in this topic [3, 4]. A channel assignment mechanism determines which channels should be allocated to which SUs. This allocation can be done via a centralized [5, 6], or distributed [7] approach. In the centralized approach, available opportunities, i.e., spectrum holes are allocated to secondary users (SUs) by a decision maker component through solving an optimization problem whereas in a distributed scheme, each SU should explore the available spectrum opportunities and make decision for exploiting the resources.

Recently, there have been a lot of works in the literature investigating the problem of channel assignment based on underlay or overlay access techniques, centralized or decentralized architecture and cooperative or non-cooperative spectrum allocation [1]. In a non-cooperative overlay CRN which is the subject of this paper, the decision for assigning SUs to primary channels should be made. A channel assignment scheme is proposed in [5], and evolutionary algorithms are used to solve the centralized allocation problem. Because of existing SUs with heterogeneous QoS requirements in CRNs, each channel should be assigned to a set of proper SUs according to their QoS requirements [8, 9]. So in this work the centralized QoS-Aware channel assignment considered as an optimization problem subject to different SUs demands and spectrum levels of QoS channel availabilities for each SU. In order to solve this optimization problem, we use evolutionary algorithms (EAs) as [5].

Evolutionary algorithms apply the principles of evolution found in nature to the problem of finding an optimal solution. Genetic algorithm (GA) and quantum genetic algorithm (QGA) are two kinds of evolutionary algorithms that are used for channel assignment in this paper. GA is an adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics. As such they represent an intelligent exploitation of a random search used to solve optimization problems and exploit historical information to direct the search into the region of better fitness within the search space [10]. Quantum evolutionary algorithms are based on the concept and principles of quantum computing such as a quantum bit and superposition of states [11], and in particular, QGA uses a qubit for representing the ordinary binary strings as using in GA. The proposed channel assignment schemes based on GA and QGA are introduced in details in the next sections of this paper.

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The rest of this paper is organized as follows: In section II we describe our system model and utility functions. Section III includes our optimization algorithms for QoS-aware channel assignment in detail. In section IV simulation results is presented, and in section V we conclude this paper and give future plan.

## II. SYSTEM MODEL AND UTILITY FUNCTIONS

### *A. System model*

A simple and general representation model of cognitive radio network environment is introduced in [5], established based on three matrices consist of availability matrix, channel benefit matrix and interference constraint matrix. In [5] the output of spectrum allocation scheme is a matrix that shows conflict free channel assignment. Our system model in this paper has inspired from this representation of communication environment, means availability and access constraint matrix and two other vectors for appending QoS-Aware properties to channel allocation scheme, named demand and resource vectors.

Consider a network with $N$ SUs indexed from 1 to $N$ competing for taking $M$ spectrum channels indexed from 1 to $M$ which are independent from orthogonality point of view. The four key components of this system model are as follows:

*Demand Vector*: $D = \{d_n\}_{1\times N}$ is a 1 by $N$ vector representing the demands of SUs in the network, where $d_n$ indicates the QoS demand of the $n$th SU.

*Resource Vector*: $R = \{r_m\}_{1\times M}$ is a 1 by $M$ vector representing the resources of channels in this scenario, where $r_m$indicates the QoS level of the $m$th channel while it can be any type of QoS such as idle time or bandwidth.

*Availability Matrix*: $L = \left\{l_{n,m} \middle| l_{n,m} \in \{0,1\}\right\}_{N\times M}$ is an $N$ by $M$ binary matrix which represents the channel availability, where $l_{n,m} = 1$ if and only if channel $m$ is available for user $n$. Unavailability of a channel for a user caused by two reasons, the first is the environmental conditions and the other one caused when $d_n > r_m$ , i.e., the demand of $n$th SU is greater than resource of $m$th channel.

*Access Constraint Matrix*: as two or more SUs may try to access the same channel simultaneously, they may have limitation on using resources of that channel. $C = \left\{c_{n,k,m} \middle| c_{n,k,m} \in \{0,1\}\right\}_{N\times N\times M}$ is an $N$ by $N$ by $M$ binary matrix for representing the interference constraint among the SUs. If $C_{n,k,m} = 1$ , users $n$ and $k$ would be access limited for accessing to channel $m$ if they use it in the same time. Two SUs $n$ and $k$ are in access limitation on channel $m$ if and only if $d_n + d - k > r_m$ , i.e., the summation of $n$th and $k$th user's demand is greater than resource of $m$th channel. Particularly$c_{n.k,m} = 1 - l_{n,m}$ if $n = k$.

*Conflict Free Channel Assignment:* $A = \left\{a_{n,m} \middle| a_{n,m} \in \{0,1\}\right\}_{N\times M}$ is an $N$ by $M$ binary matrix representing the channel assignment and $a_{n,m} = 1$ if channel $m$ is assigned to secondary user $n$. The allocation matrix $A$ needs to satisfy all the constraints determined by $C$, that is, $a_{n,m} + a_{k,m} \leq 1$ , if $c_{n,k,m} = 1$, $\forall 1 \leq n,k \leq N,\ 1 \leq m \leq M$

### *B. Utility Functions*

Given a conflict free channel assignment $A$, the assign flag vector is defined as $B = \{b_n\}_{1\times N}$ where $b_n$ is an integer variable such $b_n = \sum_{m=1}^{M} A_{n,m}$, i.e., $b_n$ is the number of channels have been assigned to $n$th SU. Assume $\Lambda_{L,C}$ is the set of all conflict free channel assignment for a given $L$ and $C$. The channel allocation problem can be written as following optimization problem:

$$A^* = \arg\max_{A\in\Lambda_{L,C}} U(R,D,A) \quad (1)$$

where $A^*$ is an optimal conflict free channel assignment matrix and $U(.)$ is a utility function of the spectrum resources and SUs demands in the network.

Now we further consider two different objective functions:

1) Channel-Utilization-Index (CUI): The objective is to maximize the total spectrum utilization in the network regardless of fairness. When the SUs occupy all spectrum opportunities and there is no white space, CUI approaches 1. CUI defined as:

$$U_{CUI}(R,D,A) = \frac{\sum_{n=1}^{N} d_n \cdot b_n}{\sum_{m=1}^{M} r_m} \quad (2)$$

2) Network-Fairness-Index (NFI): This index is defined based on Jain's fairness index [14] and depends on $x_n = \frac{b_n}{d_n}$, where $b_n$ is the number of channels have been assigned to $n$th SU and $d_n$ is the QoS demand of it. Thus a fair Qos-Aware channel assignment, allocates channels in proportion of each SU demand. When NFI approaches 1, it means that the fairness among SUs increases. NFI defined as:

$$U_{NFI}(R,D,A) = \frac{\sum_{n=1}^{N}(x_n)^2}{n \cdot \sum_{n=1}^{N} x_n^2}, \quad x_n = \frac{b_n}{d_n} \quad (3)$$

## III. OPTIMIZATION ALGORITHMS FOR QoS-AWARE CHANNEL ASSIGNMENT

### *A. Genetic Algorithm Based QoS-Aware Channel Assignment Scheme*

Genetic algorithm is a class of adaptive stochastic optimization algorithms involving search and optimization. A solution of an optimization problem is encoded in the form of a string consist of 'genes' called 'chromosome'. As introduced in [4], in the proposed channel allocation scheme based on genetic algorithm, each chromosome in the population specifies a possible conflict free channel assignment. Therefore $a_{n,m} = 0$ when $l_{n,m} = 0$ and in order to reduce the chromosome redundancy, we encode only those elements which may take the value 1, i.e., $a_{n,m} = 1$ . The length of a chromosome is equal to the number of elements in $L$ that are equal to 1 and the search space is significantly limited. The structure of an example solution (chromosome) for a network with 7 SUs and 4 channels is illustrated in Fig. 1. In this example, the solution has only 10 bits instead of encoding all 28 bits. In order to assessment of the chromosome fitness, we need to transform the chromosome to the channel assignment matrix as shown in Fig 2.

The GA-based channel assignment scheme (GA-QACAS) executes the following steps as shown in Fig. 3:

Step 1: Considering $L$ as an availability matrix, set the length of the chromosome as $\sum_{n=1}^{N}\sum_{m=1}^{M} l_{n,m}$.

Step 2: Set an initial binary population randomly.

Step 3: As shown in Fig. 2, map all the chromosomes to an assignment matrix ($A$) with this condition that, the $j$th bit of chromosome shows the value of an element in $A$ with the same position of $j$th non-zero element in $L$.

Step 4: Conflict checking: for all $m$, find all $(n, k)$ that satisfies $C_{n,k,m} = 1$, if$a_{n,m} \cdot a_{k,m} = 1$, then randomly set one of them to 0. Also if the sum of demands of SUs which attempt to occupy a specific channel $(m)$, is greater than channel QoS level, then choose a random SU ($n$th SU) and set $a_{n,m} = 0$ and repeat it until to clear all the conflicts.

Step 5: Assess the fitness of each chromosome in the population.

Step 6: Apply roulette wheel selection, two-point crossover and mutation operation.

Step 7: If the termination condition meets the maximum generation, stop; otherwise, go to step 3.

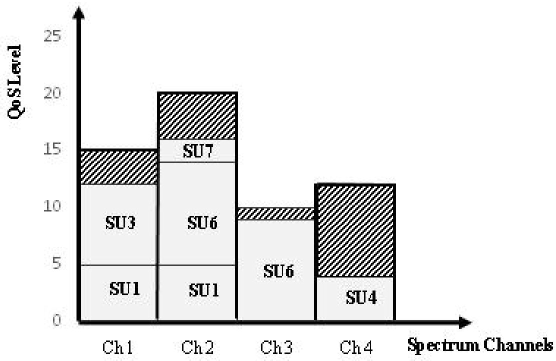


Fig. 1. An example of spectrum sharing in a network with 4 channels and 7 SUs; D=[5, 9, 7, 4, 6, 9, 2], R=[15, 20, 10, 12]. The white space in each channel is indicated by shaded region.

### *B. Quantum Genetic Algorithm Based QoS-Aware Channel Assignment Scheme*

In quantum computing, the smallest unit of information storage is the quantum bit (qubit) [3]. A qubit can be in the state 1, in the state 0 or in a superposition of both. The $i$th chromosome with $l$-qubit at the $g$th generation is represented as [4]:

$$q_i^g = \begin{bmatrix} \alpha_{i1}^g \left| \alpha_{i2}^g \right| \cdots \left| \alpha_{il}^g \right. \\ \beta_{i1}^g \left| \beta_{i2}^g \right| \cdots \left| \beta_{il}^g \right. \end{bmatrix} \quad (4)$$

where $\alpha_{ij}^g$and $\beta_{ij}^g$ must guarantee $\left|\alpha_{ij}^g\right|^2 + \left|\beta_{ij}^g\right|^2 = 1$, $i = 1, 2, \dots, P$, $j = 1, 2, \dots, l$, where $P$ is the size of population. The population of QGA can be denoted as $Q(g) = \{q_1^g, q_2^g, \dots, q_p^g\}$. Also all $\alpha_{ij}^g$and $\beta_{ij}^g$ in initial population (i.e. $g = 0$) are set to $\frac{1}{\sqrt{2}}$.

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

A solution (chromosome) G:

| $g_1$ | $g_2$ | $g_3$ | $g_4$ | $g_5$ | $g_6$ | $g_7$ | $g_8$ | $g_9$ | $g_{10}$ |
|---|---|---|---|---|---|---|---|---|---|

$$A = \begin{bmatrix} g_1 & 0 & g_2 & 0 \\ 0 & 0 & g_3 & 0 \\ g_4 & 0 & 0 & g_5 \\ 0 & 0 & 0 & g_6 \\ g_7 & 0 & 0 & 0 \\ 0 & g_8 & g_9 & 0 \\ 0 & g_{10} & 0 & 0 \end{bmatrix}$$

Fig. 2. An example solution (chromosome) structure

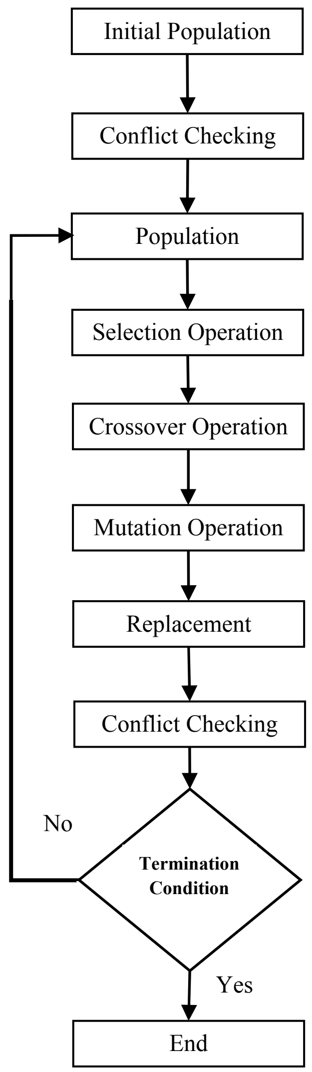


Fig. 3. Flowchart of GA-QACAS

The binary strings observed in GA as chromosomes and the qubits in the QGA play the same role and in both algorithms the utility functions $U(R, D, A)$ are used as the fitness functions directly.

The QGA-based channel assignment scheme (QGA-QACAS) executes the following steps as shown in Fig. 4:

Step 1) Similar to GA, given availability matrix $L$, set the length of the chromosome as $\sum_{n=1}^{N}\sum_{m=1}^{2} l_{n,m}$.

Step 2) Initialize $Q(g)$and make binary population $P(t)$ by observing $Q(g)$.

Step 3) As shown in Fig. 2, map all the chromosomes to an assignment matrix $(A)$ with the condition that the $j$th bit of chromosome shows the value of an element in $A$ with the same position of $j$th element in $L$.

Step 4) Conflict checking: for all $m$, find all $(n, k)$ that satisfies $c_{n,k,m} = 1$, if $a_{n,m} \cdot a_{k,m} = 1$ then randomly set one of them to 0 and if the sum of demands of SUs that attempt to access a specific channel $(m)$ is greater than channel QoS level, then choose a random SU ($n$th SU) while set $a_{n,m} = 0$ and repeat it until to clear all the conflicts.

Step 5) Assess the fitness of each individual in the $P(t)$ and store the best solution.

Step 6) if the termination condition meets the maximum generation, stop; otherwise, go to step 7.

Step 7) Increase $g$ and making $P(t)$ by observing $Q(g - 1)$.

Step 8) Repeat processes in step 3, evaluate $P(t)$, store the best solution and update $Q(t)$ using quantum rotation gate. Go to step 6.

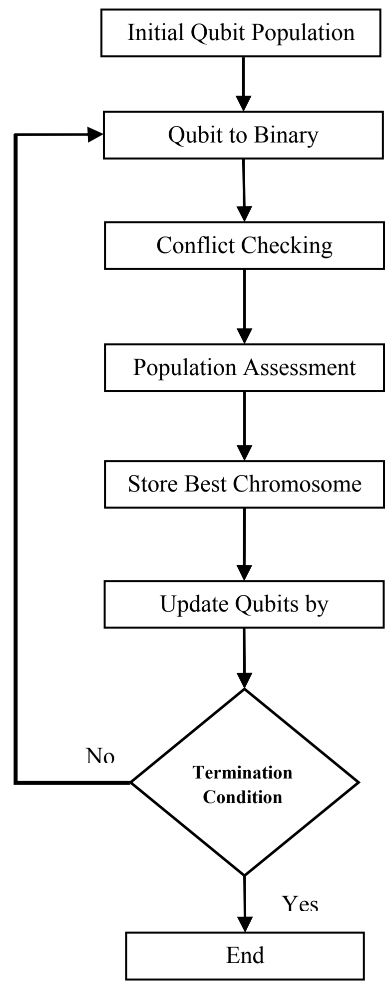


Fig. 4. Flowchart of QGA-QACAS

## IV. SIMULATION RESULTS

### A. GA and QGA parameter setting

The two proposed algorithms based on GA and QGA are configured with some parameters such that the total time of evolution is the same. For GA, the population size is set to 20, and the crossover probability and the mutation probability are set to 0.8 and 0.01, respectively. The GA is configured to replace 85% of its population in each generation, 17 of every 20 population members. As for QGA, the population size is 20 and the increment of rotation angle of quantum gates is decreased linearly from $0.1\pi$ at the first generation to $0.005\pi$ at the last generation. Both of algorithms will be terminated after 200 iterations.

TABLE I. AVERAGE UTILITY

| **Generation** | **Algorithm** | **Average Utility** | |
|---|---|---|---|
| | | ***CUI*** | ***NFI*** |
| 10 | GA-QACAS | 0.8647 | 0.6808 |
| | QGA-QACAS | 0.7919 | 0.5105 |
| 50 | GA-QACAS | 0.9554 | 0.7652 |
| | QGA-QACAS | 0.7880 | 0.5094 |
| 100 | GA-QACAS | 0.9605 | 0.7699 |
| | QGA-QACAS | 0.7832 | 0.5010 |
| 150 | GA-QACAS | 0.9604 | 0.7701 |
| | QGA-QACAS | 0.7762 | 0.5005 |
| 200 | GA-QACAS | 0.9631 | 0.7703 |
| | QGA-QACAS | 0.7824 | 0.4975 |

### B. Results and discussions

Table I shows the average rewards over 50 experiments where $N = 7$, $M = 4$, $D = [5, 7, 3, 5, 4, 10, 8]$ and $R = [10, 9, 6, 15]$. In the all experiments and for a particular objective, all of the environmental characteristics; $N$, $M$, $L$, $R$, $D$ and $C$are kept the same. The average utilities of CUI and NFI attained in each generation by GA-QACAS and QGA-QACAS are plotted in Fig. 5 and Fig. 6, respectively. We can see that the average CUI obtained by GA-QACAS after about 8 generations are better than QGA-QACAS and the average NFI. The final CUI obtained from GA-QACAS and QGA-QACAS are 96.31 % and 78.24 % respectively. It means that as a result of GA-based scheme, only about 3.69 % of spectrum left unused and it confirms the efficiency of the proposed scheme. Similar results have been achieved with NFI, so that the final NFI obtained from GA-QACAS and QGA-QACAS are 77.03% and 49.75 % in that order. It shows the better performance of GA-QACAS in fair channel assignment.

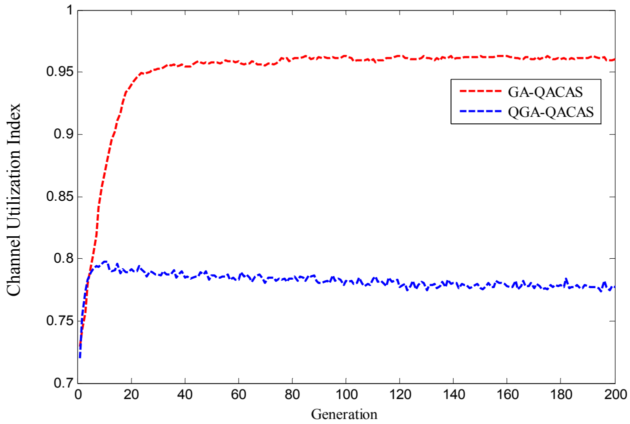

Fig. 5. Average channel utilization index: GA-QACAS vs. QGA-QACAS

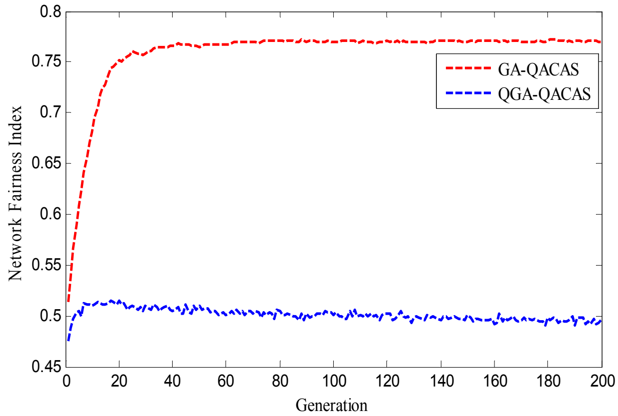

Fig. 6. Average network fairness index: GA-QACAS vs. QGA-QACAS

## V. CONCLUSION

This paper formulated the QoS-aware channel assignment in CRN as an optimization problem and proposed two EA-based schemes to solve it.The performances of two spectrum allocation schemes are compared and the results show that GA-based method greatly outperform QGA-based one under all experiments. An extension of this work is to include the trade-off between spectrum utilization and fairness among SUs. In this case an intelligent algorithm could be proposed to solve this multiobjective optimization problem.

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