Dynamic Spectrum Allocation in Cognitive Radio Using Particle Swarm Optimization

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Abstract— For efficient spectrum utilization in cognitive radio networks it requires appropriate allocation of idle frequency spectrum among coexisting cognitive radios while maximizing total bandwidth utilization and minimizing interference. The fixed spectrum allocation scheme leads to low spectrum utilization across the whole spectrum. This paper is an attempt to overcome the problem in such wireless networks with opportunistic dynamic spectrum availability and access. The base station allocates the spectrum band to the cognitive user by maximizing the total bandwidth received from all cognitive users. In this paper a Binary Particle Swarm Optimization (BPSO) algorithm is used and tested to find an optimum allocation of channels and to solve the channel assignment problem in cognitive radio network. Simulation results are compared with the conventional method and results show superiority of the optimization method.

Keywords— Bandwidth maximization, channel allocation, cognitive radio, dynamic spectrum allocation, particle swarm optimization.

I. INTRODUCTION

A cognitive radio network [1,2] automatically detects available channels in wireless spectrum, then accordingly changes its transmission or reception parameters to allow more concurrent wireless communications in a given spectrum band. Assigning of the free channels among primary and secondary users, in a specific geographic region while minimizing interference among all users is known as the Spectrum Allocation (SA) in cognitive radio networks. In Fixed Spectrum Allocation (FSA) the spectrum resources are statically allocated to the licensed users by governmental agencies or services on a long term basis. Here the unlicensed users cannot use the idle spectrum temporarily to improve the utilization efficiency. Dynamic Spectrum Access (DSA) technique [3] is a way to overcome the problem and improve inefficient fixed spectrum utilization by permitting users to dynamically sense spectrum holes [4] and use white spaces in spectrum whenever possible [Fig.1]. A spectrum hole is a band of frequencies assigned to a primary user (PU), but, at a particular time and specific geographic location, the band is not being utilized by that user.

Each cognitive user calculate a reward value corresponding to every spectrum hole depending on its requirements. These values are sent to the base station. The base station allocates the available large number of spectrum holes to the cognitive users by optimizing the total value. Several algorithm were proposed to solve the channel assignment problem using game theory [5], local bargaining [6], and vertex labelling [7]. Recently, evolutionary algorithms were also used to solve this problem; genetic algorithms [8][9], particle swarm optimization [9][10], and artificial bee colony [11].

In this paper, Particle Swarm Optimization (PSO) is used to find an optimum solution of channel assignment problem and achieve better results than the other approaches. PSO is a simple, fast and efficient computational method that optimizes a problem iteratively. As channel allocation problem requires the decision variable to be Boolean this paper proposed and tested the effectiveness (bandwidth utilization maximization) by a Binary Particle Swarm Optimization (BPSO) algorithm for optimization.

II. DYNAMIC SPECTRUM ALLOCATION

In DSA, available spectrum is divided into a set of spectrum bands and that bands differ from each other in bandwidth and transmission range.
Each secondary user keeps a list of available channels. Different secondary users are assigned different available spectrums based on its location, radio interface, and other requirements, and should be aware of its position with respect to the surrounding primary users as it cannot use a channel occupied by a primary user.

Some variables are defined as follows for system mode [12]:

1) Let N (0, 1, 2,…,N- 1) be the number of secondary users.
2) Let edges be represented by the NxN 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 same frequencies.
3) Let M (0,1,2,…,M - 1) be the number of vacant channels.
4) Let D = { d_{n} | d_{n} ∈ {0,1,2,……,M}} \_{N} is defined as the demand matrix of users, and d_{n} represents the channel capacity of user n.
5) Let L = { l_{n,m} | l_{n,m} ∈ {0, 1} \_{N×M} characterize the per user available spectrum, i.e. spectrum band m is available for user n if l_{n,m}= 1.
6) Let C = {c_{n,k,m} | c_{n,k,m} ∈ {0, 1}} \_{N×N×M} represent the interference constraint. Where if c_{n,k,m}= 1, users n and k would cause interference if they used the spectrum band m simultaneously. Here the constraints are spectrum band specific. Note that two users who are constrained by one spectrum band, they cannot use this band simultaneously.
7) Let matrix A = { a_{n,m} | a_{n,m} ∈ {0, 1} } \_{N×M} is the spectrum allocation matrix, which denotes the effectiveness of spectrum allocation. Where a_{n,m} = 1 denotes that spectrum band m is assigned to user n. A satisfies all the constraints defined by C, i.e.a_{n,m} · a_{k,m} = 0, if c_{n,k,m}= 1, ∀ n, k < N, m < M.
8) Let B = { b_{n,m} } \_{N×M} describe the reward that a user n gets by successfully acquiring available spectrum band m, i.e. b_{n,m} represents the maximum bandwidth/throughput that can be acquired (assuming no interference from other neighbors).
9) Let matrix I_{b} = { b_{n,m} } \_{N×M} represents the throughput or the bandwidth of each channel which is available for each user to use.

Performance of allocation can be expressed as follows according to the above definitions: The total bandwidth of the system is:

\[
\sum_{n=0}^{N-1} \sum_{m=0}^{M-1} a_{n,m} \cdot b_{n,m}
\]  

(1)

III. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a computational method that optimizes a problem iteratively and trying to improve a candidate solution with regard to a given measure of quality. A Swarm can be defined as a structured collection of interacting organisms (or agents). Interaction among individuals refines the experiential knowledge about the environment, and enhances the progress of the swarm toward optimality. PSO algorithm is inspired by the social behaviour of bird flocking or fish schooling [13]. In PSO, a set of particles (NP) of swarm is defined. Each particle represents a potential solution in the solution space and is characterized by its position and velocity. Each particle updates its position and velocity based on its own best position (pbest) as well as the best position of the entire swarm (gbest).

The practical implementation of classical PSO involves the following steps:

1) Parameter initialization: The dimension, range, number of particles and each particle’s initial position and velocity in the swarm is initialized to independent random values [14]. For a D-dimensional problem with N particles the position vector is represented as X(t) = (X_{1}(t), X_{2}(t), X_{3}(t), \ldots X_{D}(t)) where X_{i} = (x_{i1}, x_{i2}, x_{i3}, \ldots x_{id}) and the velocity vector is represented as V (i) = (V_{1}(t), V_{2}(t), V_{3}(t)\ldots V_{D}(t)) where V_{i} = (v_{i1}, v_{i2}, v_{i3}, \ldots v_{id}).
2) Calculate the preferred objective function of each particle based on their positions.
3) Each particle’s current fitness value is compared with previous pbest value. If the current value is better than the previous value, then set the pbest value to the current value and fix gbest of the swarm as best of all pbest.
4) Update the velocity and position of each particle according the following equations:

\[
V_{i,d}^{t+1} = V_{i,d}^{t} + c_{1} \cdot r_{1} \cdot (pbest_{i,d}^{t} - X_{i,d}^{t}) + c_{2} \cdot r_{2} \cdot (gbest_{i,d}^{t} - X_{i,d}^{t})
\]  

(2)

\[
X_{i,d}^{t+1} = X_{i,d}^{t} + V_{i,d}^{t+1}
\]  

(3)
Where ‘c1’ and ‘c2’ are the learning factors. ‘rand1’ and ‘rand2’ are independent random numbers uniformly distributed in the range [0, 1].

\[ V_{i,d}^{t+1} = W_1 \odot (pbest_{i,d} \oplus X_{i,d}^t) + W_2 \odot (gbest_{d} \oplus X_{i,d}^t) \]  
(4)

\[ X_{i,d}^{t+1} = X_{i,d}^t \oplus V_{i,d}^{t+1} \]  
(5)

\( W_1 \) and \( W_2 \) two random binary numbers which uniformly distributed in range \{0,1\};

Here, \( t \) representing number of iteration; \( i \) represents the particle’s number while solution dimension (number of variables) represented as \( d \).

IV. BPSO ALGORITHM

The schematic illustration of BPSO algorithm is shown in Fig. 2.

**Step 1**: begin

**Step 2**: Describe utilization function \( U(R) \) [equation (1)];

**Step 3**: Initialize input parameters' values: \( B \) is the reward matrix, \( N \) denotes the number of radios, \( M \) denotes the number of channels, \( P \) denotes the number of particles. \( L \) denotes channel availability.

**Step 4**: Set all particles which contain personal best solution matrix \( pbest_{ij} \), current solution matrix \( currentsol_{ij} \), global solution matrix \( gbest_{ij} \) and velocity matrix \( vel_{ij} \) to zeroes where \( 0 < i \leq N \) and \( 0 < j \leq M \).

**Step 5**: For \( t < \) max number of iterations) map the \( j \)th element in \( L \) where \( 1 < j < L \) for all particles. For all \( m \), search all \( (n; k) \) that satisfies \( C_{n,k,m} = 1 \), and check if \( a_{n,m} = a_{k,m} = 1 \), then randomly set one of them to 0.

**Step 6**: Evaluate each particle's position according to the objective function \( U(R) \).

**Step 7**: If a particle's current position is better than its previous best Position, update it. Fix the best particle (according to the particle’s previous best positions).

**Step 8**: Update particles' velocities according to equation (4) and move particles to their new positions according to equation (5).

**Step 9**: Find the current best solution i.e. the optimum value then End.

Fig. 2. Schematic illustration of BPSO algorithm

V. APPLICATION OF PSO IN DSA

For the application PSO in dynamic spectrum allocation, equation (1) is used as cost function.
Simulation results of Spectrum Allocation using Binary Particle Swarm Optimization (BPSO) are presented in Fig. 3 to Fig. 8. Different combinations of number of cognitive radios and available channels are considered for experimental study. It is assumed that standard algorithmic parameters for BPSO as c1 and c2 as 2.0. The proposed BPSO algorithm executed in multiple rounds for resource allocation. In each round, one channel is allotted to one radio satisfying the channel requirement constraints while maximizing the total bandwidth value. The available reward value for each node for a particular channel is taken random.

There are three different scenarios for allocation with fixed no of particles such that (i) no of cognitive user = no of available channel, (ii) no of cognitive user > no of available channel, (iii) no of cognitive user < no of available channel.

Let M= the number of radios, C= the number of channels, P= the number of particles

i) Using BPSO algorithm in MATLAB for M= 5, C=5, P=3 the maximum bandwidth utilization (5.1183) for spectrum allocation.

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ii) For M= 5, C=8, P=3 the maximum bandwidth utilization (9.1506) for spectrum allocation.

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iii) For M= 8, C=5, P=3 the maximum bandwidth utilization (7.4552) for spectrum allocation.

VI. RESULTS

A. Using BPSO the maximum bandwidth value is optimized and plot the gbest value i.e. the maximum value with the different iteration no for fixed no of radio and channels.

![Fig. 3. Convergence of gbest value for no of cognitive user = no of available channel(for M=5, C=5, P=3)](image)

In this plot gbest(max)=12.9846, gbest(min)=3.1619. So range=9.8227.
From the above three graphs it can be concluded that Binary PSO is giving better solutions when the number of radios are equal to the number of available channels for allocation. As with the increasing no of iteration the first condition gives deviation of gbest (max) with a minimum range than others. It converges at the iteration no. 700 (Fig. 3), where as in case ii) (Fig.4) convergence occurred at the iteration no.8000 and in case iii) convergence occurred at the iteration no.5000 (Fig.5).

B. Using BPSO the maximum bandwidth value i.e. gbest is optimized and plot the gbest value with the different no. of cognitive users for fixed no of available channels, particles and fixed no of iterations and compare them with the conventional method.

In this plot $\text{gbest}_{\text{max}}$ (without using PSO)= 21.5496, $\text{gbest}_{\text{max}}$ (using PSO)= 21.6852. So improvement=0.1356.

In this plot $\text{gbest}_{\text{max}}$ (without using PSO)= 19.7996, $\text{gbest}_{\text{max}}$ (using PSO)= 20.902. So improvement=1.1024.
Fig. 8. Optimized gbest value for different no of cognitive user using BPSO (for C=10, P=5, Iteration no.=10000)

In this plot gbest_{max} (without using BPSO)= 18.9059, gbest_{max} (using PSO)= 27.8406. So improvement=8.9347.

From Fig. 6 to Fig. 8, it can be concluded that for fixed no of channels if the no of cognitive users is increasing the deviation of gbest value is minimized and after a certain value gbest is saturates for any no of cognitive users afterwards. Here, Spectrum allocation method using BPSO is compared with the conventional method without using BPSO. For Fig. 6 when C=20 bandwidth utilization is maximized in spectrum allocation with or without using BPSO more or less same. But In Fig. 7 when C=15 it has shown that bandwidth utilization maximized in spectrum allocation using PSO improved by 1.1024 and in Fig. 8 when C=10 the improvement is high as 8.9347. So it can be concluded that for the least no of channel the improvement of gbest value is increasing by BPSO optimization i.e bandwidth is utilized maximum and gives better result. Here the effectiveness (utilization function maximization) is tested.

VII. CONCLUSION

Dynamic channel allocation is optimized using Binary Particle Swarm Optimization algorithm to test the effectiveness (utilization function maximization) and to solve the channel assignment problem in cognitive radio networks. The simulation results presented in the paper show a superior performance of the proposed algorithm compared to those reported in the literature with respect to maximum bandwidth utilization. It gives better result for least number of channels and practically cognitive radio get least number of channels.

Here the algorithm only considers a single secondary user scenario that is each SU can require only one channel of suitable bandwidth, but in practical applications, multi-secondary user scenario will be mainly considered for the dynamic spectrum allocation algorithm in future. In this work, it is assumed that the environment is static. If environment changes, network-wide spectrum allocation has to be performed. This leads to significant overhead and delay.

REFERENCES


