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TLBO BASED SPECTRUM ALLOCATION IN COGNITIVE RADIO NETWORK

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Abstract:

Cognitive Radio Networks (CRNs) have emerged as a solution for the problems created due to fixed spectrum allocation such as inefficient usage of licensed spectrum. CRNs aim at solving this problem by exploiting the spectrum holes (the spectrum not being used by primary radio nodes at a particular time) and allocating spectrum dynamically. In this work, a heuristic Teaching and Learning Based Optimization (TLBO) algorithm is used for solving Spectrum Allocation (SA) problem. The performance of TLBO algorithm is compared with Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms in terms of equality of solution (network capacity) and timing complexity. The whole system is simulated in MatLab and compares the performance with PSO and ABC algorithm.

Keywords: Cognitive Radio Networks, Spectrum Allocation, Teaching-Learning-Based optimization algorithm, Particle swarm Optimization algorithm, Artificial Bee Colony algorithm, Mat Lab.

I. INTRODUCTION:

During the past few years mobiles, smartphones and wireless devices are playing more prominent role in our daily lives, we demanded to be connected to single or multiple users at anyone, anywhere and anytime without much delay.

The fixed spectrum allocation strategy in existing wireless networks is extremely inefficient. The spectrum of the wireless networks is generally regulated by governments via a fixed spectrum assignment policy. CRNs introduced to overcome the utilization of spectrum in a proper manner. It is a new paradigm for wireless communication that allows spectrum deficiency to be exploited in an opportunistic manner. Unless the traffic is continuous and uniform, an assignment spectrum band is always underutilized or even unused, leading to a waste of radio resources. These underutilized or unused spectrum bands are called spectrum holes (also called white spaces). Actually there are two types of spectrum holes. Type-1 spectrum hole is the portion of underutilized assigned spectrum, the usage of a particular assigned spectrum over a period of time. Assume that the maximum throughput for this band is 20 Mbps; the spectrum band is rarely being fully utilized, leaving lots of white spaces. We call this underutilized white spaces type-1 spectrum holes. Taking advantage of such spectrum requires sophisticated spectrum spreading. Type-2 spectrum hole is the gap between transmissions in an assigned spectrum. The spectrum band is being used to its full capacity, but there are pauses in the transmission, creating lots of white spaces. We call these gaps type-2 spectrum holes. This type of spectrum hole is much easier to detect and utilize. In reality, type-1 and type-2 often co-exist in an assigned spectrum band while type-1 occurs more often than type-2. In fixed spectrum assignment, these spectrum holes could fill up to 85% of the assigned band. The observation of spectrum holes inspired the introduction to cognitive radio technologies.

The approach to address type-1 spectrum hole is called underlay, in which an unlicensed user might transmit in the same band and at the same time as the licensed user, as long as their interference is within tolerable limit of the licensed user. The approach to address type-2 spectrum hole is called overlay, in which an unlicensed user only transmits when the band is not in use, causing minimum interference to the licensed user. These licensed and unlicensed users are actually called primary user (PU) and secondary user (SU), respectively. Formally, a PU is the subscriber of a licensed band network, and an SU is the one that leases the unused licensed band of the network. In essence, a PU and an SU share the same spectrum band, typically in a preemptive manner where priority is given to the PU. In other words, if a PU requests a spectrum band that is currently used by an SU, this SU must vacate the band immediately and either migrate to another spectrum hole or has to hang up. Such preemptive sharing scheme is widely accepted for the purpose of avoiding harmful interference to existing PUs.

The key challenge of constructing a CRN is to detect spectrum holes and assign them to appropriate users. Therefore, besides the conventional network management functions like admission control, congestion control, and handover, a CRN must implement at least two additional functions:

- Spectrum sensing - detecting spectrum holes in the licensed spectrum bands; and
- Spectrum sharing - deciding proper spectrum allocation scheme among existing PUs and SUs. This is also called the spectrum assignment.

II. Spectrum Allocation Model In Cognitive Radio Networks:

Spectrum allocation model

The general spectrum allocation model presented in [9] consists of channel availability matrix, channel reward matrix, interference constraint matrix and conflict free channel assignment matrix. Assume a network of N secondary users indexed from 1 to N competing for M spectrum channels indexed from 1 to M which are non-overlapping orthogonal.

The channel availability matrix $L = \{l_{n,m} \mid l_{n,m} \in \{0,1\}\} N \times M$ is an N by M *binary* matrix representing the channel availability, where $l_{n,m}$ = 1 if and only if channel m is available to user n, and $l_{n,m}$ = 0 otherwise. The channel reward matrix $B = \{b_{n,m}\} N \times M$ is an N by matrix representing the channel reward, where $b_{n,m}$ represents the reward that can be obtained by user n using channel m. As two or more secondary users may use the same channel at the same time, they may interfere with one another. The interference constraint matrix $C = \{c_{n,k,m} \mid c_{n,k,m} \in \{0,1\}\} N \times N \times M$ is an N by N by M matrix representing the interference constraint among secondary users, where $c_{n,k,m}$ = 1 if users n and k would interfere with each other if they use channel m simultaneously and $c_{n,k,m}$ = 0 otherwise. In particular, $c_{n,k,m} = 1 - l_{n,m}$ if $n = k$.

In real applications, the spectrum environment varies slowly while users quickly perform network-wide spectrum allocation. We assume that the location, available spectrum, etc. are static during the spectrum allocation, thus L, B, and C are constant in an allocation period.

The conflict free channel assignment matrix $A=\{a_{n,m} \mid a_{n,m} \in \{0,1\}\}N \times M$ represents the channel assignment, where $a_{n,m}$ = 1 if channel *m* is allocated to secondary user *n*, and $a_{n,m}$ = 0 otherwise. *A* must satisfy the interference constraints defined by *C*:

$$a_{n,m} \cdot a_{n,k} = 0,\ if\ c_{n,m} = 1, \forall 1 \le n,k \le N, 1 \le m \le M. \quad (1)$$

Given a conflict free channel assignment, the reward user *n* gets is defined as $r_n = \sum_{m=1}^{M} a_{n,m} \cdot b_{n,m}$. We use $R = \left\{ r_n = \sum_{m=1}^{M} a_{n,m} \cdot b_{n,m} \right\} N \times 1$ to represent the reward vector that each user gets for a given channel assignment. Let $\wedge_{L,C}$ be the set of conflict free channel assignment for a given *L* and *C*. The spectrum allocation is to maximize network utilization *U* (*R*). Given the model above, the spectrum allocation problem can be defined as the following optimization problem [9]:

$$A^* = \arg\max_{A \in \wedge_{L,C}} U(R), \quad (2)$$

where A^* is the optimal conflict free channel assignment matrix. In this paper, we consider three objective functions as in [9]:

(1) Max-Sum-Reward (MSR): $U(R) = \sum_{n=1}^{N} r_n$,

(2) Max-Min-Reward (MMR): $U(R) = \min_{1 \le n \le N} r_n$, and

(3) Max-Proportional-Fair (MPF): $U(R) = \left(\prod_{n=1}^{N} \left(r_n + 10^{-6} \right) \right)^{\frac{1}{N}}$.

III. TLBO ALGORITHM:

Teaching-learning is an important process where every individual tries to learn something from other individuals to improve themselves. Rao et al. [6] and [7] and Rao and Patel [8] proposed an algorithm, known as Teaching-Learning-Based Optimization (TLBO), which simulates the traditional teaching-learning phenomenon of a classroom. The algorithm simulates two fundamental modes of learning: (i) through the teacher (known as the teacher phase) and (ii) interacting with other learners (known as the learner phase). TLBO is a population-based algorithm, where a group of students (i.e. learner) is considered the population and the different subjects offered to the learners are analogous with the different design variables of the optimization problem. The results of the learner are analogous to the fitness value of the optimization problem. The best solution in the entire population is considered as the teacher. The operation of the TLBO algorithm is explained below with the teacher phase and learner phase [8].

A. Teacher phase

This phase of the algorithm simulates the learning of the students (i.e. learners) through the teacher. During this phase, a teacher conveys knowledge among the learners and makes an effort to increase the mean result of the class. Suppose there are 'm' number of subjects (i.e. design variables) offered to 'n' number of learners (i.e. population size, $k = 1,2,\ldots,n$). At any sequential teaching-learning cycle, $i, M_{j,i}$ is the mean result of the learners in a particular subject 'j' ($j = 1,2,\ldots,m$). Since a teacher is the most experienced and knowledgeable person on a subject, the best learner in the entire population is considered a teacher in the algorithm. Let $X_{total-kbest,i}$ be the result of the best learner considering all the subjects who is identified as a teacher for that cycle. The teacher will put maximum effort into increasing the knowledge level of the whole class, but learners will gain knowledge according to the quality of teaching delivered by a teacher and the quality of learners present in the class. Considering this fact, the difference between the result of the teacher and the mean result of the learners in each subject is expressed as:

$$Difference\_Mean_{j,i} = r_i\left(X_{j,kbest,i} - T_F M_{j,i}\right), \tag{3}$$

Where $X_{j,kbest,i}$ is the result of the teacher (i.e. best learner) in subject j. T_F is the teaching factor, which decides the value of mean to be changed, and r_i is the random number in the range [0,1]. The value of T_F can be either 1 or 2. The value of T_F is decided randomly with equal probability as:

$$T_F = round\left[1 + rand(0,1)\{2-1\}\right], \tag{4}$$

where $rand$ is the random number in the range [0, 1]. T_F is not a parameter of the TLBO algorithm. The value of T_F is not given as an input to the algorithm and its value is randomly decided by the algorithm using Eq. (4).

Based on the $Difference\_Mean_{j,i}$, the existing solution is updated in the teacher phase according to the following expression:

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,i} \tag{5}$$

Where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$. Accept $X'_{j,k,i}$ if it gives a better function value. All the accepted function values at the end of the teacher phase are maintained, and these values become the input to the learner phase.

It may be noted that the values of r_i and T_F affect the performance of the TLBO algorithm. r_i is the random number in the range [0, 1] and T_F is the teaching factor. However, the values of r_i and T_F are generated randomly in the algorithm and these parameters are not supplied as input to the algorithm (unlike supplying crossover and mutation probabilities in GA, inertia weight and cognitive and social parameters in PSO, and colony size and limit in ABC, etc.). Thus, tuning of r_i and T_F is not required in the TLBO algorithm (unlike the tuning of crossover and mutation probabilities in GA, inertia weight and cognitive and social parameters in PSO, and colony size and limit in ABC, etc.). TLBO requires tuning of only the common control parameters, like population size and number of generations, for its working, and these common control parameters are required for the working of all population based optimization algorithms. Thus, TLBO can be called an algorithm-specific parameter-less algorithm.

B. Learner phase

This phase of the algorithm simulates the learning of the students (i.e. learners) through interaction among themselves. The students can also gain knowledge by discussing and interacting with other students. A learner will learn new information if the other learners have more knowledge than him or her. The learning phenomenon of this phase is expressed below.

Randomly select two learners, P and Q, such that $X'_{total-P,i} \neq X'_{total-Q,i}$, where, $X'_{total-P,i}$ and $X'_{total-Q,i}$ are the updated values of $X_{total-P,i}$ and $X_{total-Q,i}$, respectively, at the end of the teacher phase.

$$X''_{j,P,i} = X'_{j,P,i} + r_i\left(X'_{j,P,i} - X'_{j,Q,i}\right), \text{ If } X'_{total-P,i} > X'_{total-Q,i} \tag{6a}$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i\left(X'_{j,Q,i} - X'_{j,P,i}\right) \text{ If } X'_{total-Q,i} > X'_{total-P,i} \quad (6b)$$

(The above equations are for maximization problems, the reverse is true for minimization problems.)

Accept $X''_{j,P,i}$ if it gives a better function value.

IV. Spectrum Allocation using TLBO Algorithm:

In TLBO, the teacher phase and student phase are there. For teacher phase, to find the mean of the students by using random values through the number of students and the number of design variables (or) number of subjects which are taken by students are calculate by the summation of channel availability, these channel availability can be solved by using the distance between the primary user and secondary user, secondary user and secondary user with a given radius which are not interfere each other. Capturing the teacher position by using the channels and secondary user information's and then find the best teacher which have more knowledge on subjects and then update it till to get the best value. Difference mean of the total number of design variables can be solved by taking the random values through the updated best teacher and the mean of the students. Check the upper limit and lower limit values for improving the teacher phase in an iteration of number of design variables. Keep updating till to get best value.

For learner phase, calculate the best learner among the learners through the channels and secondary users objective function values and update the values by using number of design variables. Improving the level other learners using best learner and update the objective function which are define by using the channels and secondary user information's. These objective functions can be calculate by the Max Sum Reward (MSR), Max Min Reward (MMR) and Max-Proportional-Fair (MPF)

V. Experimental Setup:

In this paper, we choose the parameters of the Teaching-Learning Based Optimization algorithm such that the total times of fitness evaluation is the same in the three algorithms. For TLBO, the number of students is 50, number of design variables (or) number of subjects which are taken by students are calculated through the summation of channel availability matrix. In PSO, the number of particles in a swarm is set to 20, the two acceleration coefficients [10] are equal to 2, and $Vmax = 4$. All the three algorithms will be terminated after 200 iterations (generations).

VI. Results:

In this section we presented the convergence results for solving the spectrum allocation problem using three optimization algorithms namely, TLBO, ABC and PSO algorithms. The experiment is run for 20 independent runs and the final results shown in the Fig. 1, Fig. 2 and Fig. 3.

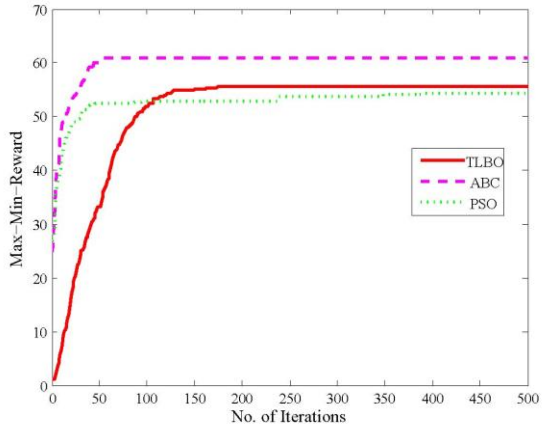

Fig. 1: No. of Iterations Vs. Max-Min Reward

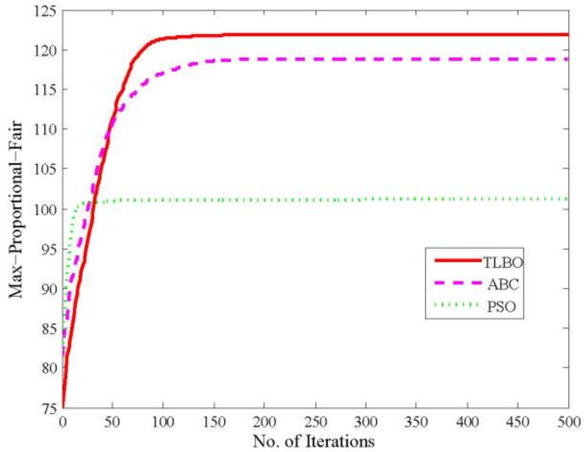

Fig. 2: No. of Iterations Vs. Max Proportional Fair

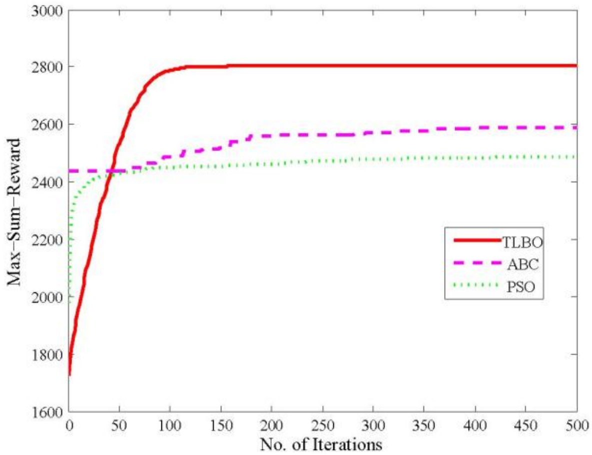

Fig. 3: No. of Iterations vs. Max-Sum Reward

VII. CONCLUSION:

In this work, spectrum allocation problem is solved by using new algorithm called Teaching and Learning based optimization algorithm. We optimized the three network utilization functions Max-Sum-Reward (MSR), Max-Min-Reward (MMR) and Max-Proportional-Fair (MPF) are maximized by satisfying the interference constraints posed by primary user and secondary users. To compare the performance of TLBO algorithm, same problem is solved by using the ABC and PSO algorithms. From the results, it is observed that the TLBO algorithm performs better than ABC and PSO algorithms.

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