Swarm and Evolutionary Computation 36 (2017) 1–17

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

Intelligent dynamic spectrum access using hybrid genetic operators

Md. Jahidul Islam[a,b,*], Md. Monirul Islam[b], A.B.M. Alim Al Islam[b]

[a] *Department of Computer Science and Engineering, University of Minnesota, Twin Cities, MN 55455, USA*
[b] *Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, Dhaka 1000, Bangladesh*

ARTICLE INFO

Keywords:
Dynamic spectrum access
Hybrid genetic operators
Cognitive radio networks

ABSTRACT

This paper presents a novel hybrid dynamic spectrum access approach, combining classical and stochastic flavors being augmented with new genetic operators, for multi-channel single-radio cognitive radio networks. Existing classical and stochastic approaches exhibit different advantages and disadvantages depending on network architecture. Our proposed approach exploits a delicate balance between the two different approaches for extracting advantages from both of them while limiting their disadvantages. Additionally, in our proposed approach, we boost up extent of the exploitation through designing new genetic operators.

Furthermore, we provide a thorough performance evaluation of our approach using a widely used discrete event simulator called `ns-2`. Here, we also simulate several existing approaches that are based on graph theory, game theory, heuristic, genetic algorithm, agent-based learning, and online learning. Simulation results demonstrate significant performance improvement using our proposed intelligent dynamic spectrum access approach over these state-of-the-art ones based on various standard metrics.

1. Introduction

Radio spectrum is a natural, however, limited resource regulated by governmental or international agencies. Most parts of the spectrum are assigned to license holders known as *Primary Users (PUs)* on a long-term basis using a fixed spectrum assignment policy [1,2]. Remaining parts of the spectrum are open to unlicensed users known as *Secondary Users (SUs)*. The SUs are allowed to use temporarily-unused portions of the spectrum [3–7] without interfering with the PUs. Cognitive Radio (CR) technology [3,8] enables this opportunistic spectrum access, which is termed as Dynamic Spectrum Access (DSA).

DSA [3,8,7] provides the basic functionality of CR networks (CRNs) through opportunistically assigning the most appropriate spectrum fragment to CR devices while ensuring avoidance of interference with any PU. Due to these operating constraints, traditional channel assignment techniques for wireless mesh networks [9] are not readily applicable for DSA in CRNs. The underlying mechanism of DSA in CRNs requires the following four core functionalities:

i. **Spectrum Sensing:** Identification of unused spectrum fragments (also termed as *spectrum holes* [10]),
ii. **Spectrum Selection Decision:** Selection of the best available spectrum fragment according to some criteria [3] (such as minimizing interference, increasing network throughput, etc.),
iii. **Spectrum Mobility:** Vacating a spectrum when a PU within the same operational region wants to access the same spectrum, on which current transmission of the SU is going on, and
iv. **Spectrum Sharing:** Coordinating access to the spectrum fragments being used by other SUs.

DSA in CRNs has been widely studied in recent years. Graph theory based algorithms [11–13] are the most commonly used classical approaches in this regard. However, most of these approaches consider networks having only SUs [3]. Such sole consideration of SUs, ignoring the presence of PUs, is not suitable for pragmatic deployment of CRNs. Another important class of approaches for DSA is based on game theory [14–16]. Here, utility function and game formulation used in these approaches must be very carefully structured to achieve equilibrium, which is not always guaranteed. In addition to these approaches, agent-based learning [17], Artificial Neural Network [18], and fuzzy logic based approaches are proposed in recent studies. Agent-based learning approaches demand problem specific designs, while the approaches based on linear programming adopt few assumptions that are not always valid in reality. Besides, a fuzzy system is not scalable as a large number of rules are required for performing DSA considering all different parameters that can affect the DSA decision.

As the DSA problem belongs to the class of NP-complete problems [3], all the approaches mentioned above demand high computational overhead with an increasing number of CR users. Therefore, DSA approaches based on heuristic search [19,20] and evolutionary algorithms [21,22] are

* Corresponding author at: Department of Computer Science and Engineering, University of Minnesota, Twin Cities, MN 55455, USA.
E-mail addresses: islam034@umn.edu (Md. J. Islam), mdmonirulislam@cse.buet.ac.bd (Md. M. Islam), alim_razi@cse.buet.ac.bd (A.B.M. Alim Al Islam).

http://dx.doi.org/10.1016/j.swevo.2017.03.004
Received 18 July 2016; Received in revised form 12 March 2017; Accepted 31 March 2017
Available online 05 April 2017
2210-6502/

more effective for large-scale CRNs as they are less sensitive to variations in problem characteristics and dimensionality. A family of meta-heuristic and evolutionary algorithms are extensively used in several other applications [23–26] such as signal processing and filtering to overcome similar scalability problem. Moreover, these algorithms are computationally efficient for finding optimal solutions [27–29] in dynamic search-spaces with reasonable success rate. However, one major issue of such stochastic approaches is that they often get stuck in locally optimal solutions, which, in case of CRNs, can lead to very poor spectrum utilization. Consequently, the two classes of approaches for DSA, i.e., classical approaches and stochastic approaches, exhibit different advantages and disadvantages. Additionally, although using a blend of classical local search and stochastic methods facilitates better avoidance of locally optimal solutions and faster convergence in many optimization problems [30], such hybrid approaches are yet to be focused for DSA in CRNs. Moreover, even though there are several approaches proposed for DSA, proper and thorough performance evaluation of these approaches using a discrete event simulator is yet to be performed in the literature. These methods are mostly evaluated through numerical simulations, to date.

In this work, we address all the issues mentioned above. We devise an intelligent DSA algorithm by exploiting a synergy between a Genetic Algorithm (GA)-based stochastic method and classical local search-based novel genetic operators. Afterwards, we evaluate performance of the proposed mechanism along with that of other state-of-the-art algorithms in `ns-2`. Based on our work, we make the following set of contributions in this paper:

- We conduct a thorough performance evaluation of the basic genetic operators and parameter values using discrete event simulation. This empirical study reveals a combination of genetic operators and parameter values that performs the best with GA-based DSA. For performance evaluation, we use *Cognitive Radio Cognitive Network (CRCN) simulator* [31], which is based on ns-2. We perform necessary modifications [32] in the basic CRCN simulator to enable spectrum sharing and spectrum mobility features in our evaluation. The modified simulator can be exploited for future research purposes to evaluate performance of DSA algorithms in CRNs.
- Subsequently, we devise two novel hybrid genetic operators named neighborhood-based crossover and local search based survivor selection, which demonstrate significantly better performance than the previously proposed best combinations of genetic operators. Our hybrid genetic operators, along with the tuned-up parameter values, result in a highly scalable and efficient DSA technique (we name it GALS) for multi-channel single-radio CRNs.
- Using CRCN simulator, we evaluate the performance of GALS on the basis of various standard performance metrics. We compare its performance with that of several widely-used DSA approaches, which are based on graph theory, game theory, heuristics, genetic algorithm, agent-based learning, and online learning. Simulation results suggest significant performance improvement using GALS compared to these state-of-the-art algorithms. In particular, GALS demonstrates remarkable performance improvement on fairness over the network, which is considered as the most challenging performance metric to improve in distributed CRNs [3,33].

The rest of the paper is organized as follows: Section 2 elaborates on background of the DSA problem and analyzes it from different viewpoints. Then, Section 3 presents our network model and summarizes modifications that we performed in the basic CRCN simulator. Next to that, Section 4 investigates the performance of GA-based DSA with different combinations of basic genetic operators. Subsequently, Section 5 discusses the design of our novel genetic operators and Section 6 presents the algorithm of GALS. Finally, Section 7 provides a comprehensive analysis of the performance of GALS compared to other state-of-the-art algorithms. At last, Section 8 draws conclusions and highlights possible future research directions.

2. Background and related work

There are a number of research studies that demonstrate various DSA approaches. We present these approaches according to three different points of view - architecture, spectrum sharing, and algorithm.

2.1. Architectural viewpoint

CRNs can operate in either centralized or distributed mode. Consequently, the operational architecture of spectrum management approaches can be either centralized or distributed.

Centralized DSA approaches [33,34] require a central entity to make spectrum assignment decisions. In centralized DSA, it is easier to maximize overall network throughput, minimize interference between SUs, and maintain network connectivity, as the central node has a global view of the network. On the other hand, a major disadvantage of centralized DSA is that it induces signalling overhead in the network owing to the need of exchanging information between the SUs and the central entity.

In distributed DSA [11,35], no central entity is available to make spectrum assignment decisions. In this case, the CR users take decisions either by themselves or by cooperating with their neighbors. Distributed DSA approaches are usually more flexible and incur lower signalling overhead in the network. However, fairness is a major concern for such approaches [3], since CR users do not have any global view of the network.

2.2. Spectrum sharing viewpoint

Considering access technology and sharing methodology, spectrum sharing mode can be categorized in two types [3]: *overlay spectrum sharing* and *underlay spectrum sharing*. In overlay spectrum sharing, SUs access only the portions of the spectrum that are not being used by any PU. On the other hand, in underlay spectrum sharing, SUs can access spectrum bands that are currently being used by PUs and SU-transmissions are regarded as noise by the PUs. Furthermore, spectrum sharing can be *cooperative* or *non-cooperative*, depending on whether or not, the CR users (both PUs and SUs) communicate among themselves for spectrum access decisions.

2.3. Algorithmic viewpoint

Irrespective of architecture and mode of spectrum sharing, existing DSA techniques can be classified into several categories based on their underlying algorithms. Like channel assignment algorithms for wireless mesh networks [9], DSA algorithms for CRNs cover graph theory, game theory, heuristics, evolutionary algorithms, etc.

Graph Theory based approaches [11,36,13] visualize the network as a graph where the vertices correspond to CR users and edges correspond to connections among them. Such approaches generally construct *network conflict graph* [3] to capture interference between neighboring SUs [11,36]. These approaches also use graph coloring [13,19,20], where the DSA problem is mapped into a graph coloring

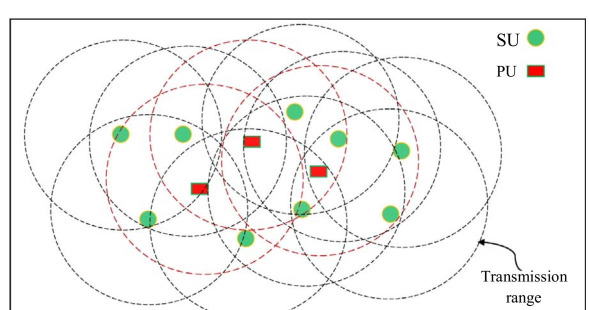

Fig. 1. Our CRN model comprising PUs and SUs.