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Intelligent control of cognitive radio parameter adaption: Using evolutionary multi-objective algorithm based on user preference

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ABSTRACT

Cognitive radio (CR) is a promising technique for overcoming the spectrum scarcity problem. It must appropriately alter its transmission parameters according to predefined objectives in dynamic wireless environment. In this paper, we model the CR parameter adaptation problem as an unconstrained multi-objective optimization problem and then propose a non-dominated front searching algorithm based on user preference (NFSA-UP) to determine the optimal transmission parameters for a multicarrier system. The distances from individuals to the user preference direction are combined with the pareto ranks to determine the evolving direction as well as the survive selection of individuals. It is beneficial to increase selection pressure at the beginning of the evolving, and speed up convergence to the true pareto optimal front at end. The best individual which is obtained after final iteration is reported here as the middle point on the first pareto front, avoiding the secondary selection from a set of optimal solutions. We performed multi-objective optimization on a 64 subcarriers in CR network. NFSA-UP is compared with other pareto front searching algorithms NSGAII and NSGAII-LBS, and the results demonstrate that the optimal transmission parameters of CR can be got using NFSA-UP with any user preference direction, while better performance is observed.

1. Introduction

The increasing growth of wireless services over the last decade demonstrates the vast demand for radio bands. However, the spectrum resource is limited and mostly has been licensed to users which can work within a limited frequency band [26]. The studies by the Federal Communication Commission have found that the actual licensed spectrum is largely unoccupied most of the time [7]. In order to deal with the imbalance between spectrum scarcity and spectrum under utilization, cognitive radio technology was proposed [15].

Cognitive radio is a promising technique for overcoming the apparent spectrum scarcity problem, as well as improving the communications efficiency [27,9]. The IEEE has formed the 802.22 Working Group to develop a standard for wireless regional area networks (WRAN) based on cognitive radio technology [10]. Ideally a Cognitive Radio (CR) possesses the capability of sensing, perceiving, decision making, planning, and learning in a wireless environment [6]. Due to the time varying radio channel characteristics, as well as the spectrum band availability, cognitive radios need to support time varying Quality of Service (QoS) requirements. Even though the principal goal of dynamic spectrum access (DSA) is to improve the spectrum utilization efficiency, other goals such as minimizing the bit-error-rate (BER), maximizing the data throughput,

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minimizing the power consumption, also need to be met [1].

Therefore, cognitive radio (CR) must be able to sense the environment periodically and appropriately alter the transmission parameters according to the objectives and QoS requirements of the users [22]. To achieve these goals, CR needs a cognitive engine to be aware of its environment, including the transmission link, user demands, and regulatory regimes, and it must balance multiple objectives. This learning characteristic of CR makes it intelligent that adapts itself in the dynamic situations [6,1,22].

Evolutionary multi-objective optimization (EMO) algorithms are well suited to solving multi-objective optimization and decision problems [11,14], and it has been shown that a EMO based cognitive radio engine can support awareness-processing, decision-making, and learning elements of cognitive functionality [21]. Research done at Virginia Tech has developed a genetic algorithm (GA) engine for cognitive radios [1]. Their simulation results validate that the genetic algorithm implementation does in fact change the transmission parameters to different settings, based upon a set of objectives. A set of single carrier and multicarrier fitness functions have been derived and GA is used to search the optimal set of transmission parameters in [16]. Adaptive transmission in the context of cognitive radio networks is addressed in [28] where GA is used to optimize the CR parameters by considering several QoS and channel coding schemes. In order to reduce the convergence time and to improve the optimization results of spectrum utilization, in [17] a population adaptation technique for reducing the amount of time required to reach an optimal decision for a GA-based cognitive engine is proposed. And a technique using quantized variables with adaptive variable ranges, based on the knowledge gathered from previous experience, is studied in [1]. These two methods both assumed that the wireless channel environment changes slowly, such that the gathered knowledge can be reused in the near future.

All the above works have attempted to solve the parameter adaptation problem in CR by formulating it into single objective functions using weighted sum approach. When a multi-objective optimization problem is solved by weight vector aggregate sum approach, the result will find a single value for each parameter and thus the behavior of solution space cannot be deduced with respect to multiple objective functions. For the real-time scenario, the performance of CR system depends on the choice of weights to specific objective functions which is hard and scenario dependent [6]. Therefore, Tosh et al. model the CR parameter adaptation problem as an unconstrained multi-objective optimization problem and perform optimization of more than one conflicting objectives at a time using Non-dominated Sorting-based Genetic Algorithm (NSGA-II) instead of weighted sum approach [6]. This helps to find a set of optimal solutions from the large range of solution space defined in terms of pareto optimal set. NSGA-II avoided the setting of the weight vectors and got more accurate solutions than GA. However, for NSGA-II there are a set of optimal solutions on the pareto-front, which are all non-dominated, thus the choice of best solution needs a further comparison, and it takes more time to get coverage [5].

In the real applications of multi-objective optimization, the decision makers usually have some preference on the fitness functions. For example, they may want the fitness functions to coverage to given target values, and these preference information can be used to direct the evolutionary procedure [24]. Fonseca and Fleming probably suggested the earliest attempt to incorporate preferences, and their proposal was to use EMO together with goal information as an additional criterion to assign ranks to the members of a population [8]. Shaw and Fleming incorporate the target information into the calculation of fitness to design a preference based multi-objective optimization algorithm to solve the production scheduling problem [23]. Pierro et al. proposed preference order mechanism to discriminate non-dominate solutions [20]. Cvetkovic and Parmee [3] used binary preference relations (translated into weights) to narrow the search. In [25], preferences were included through the use of reference points. Also a guided dominance scheme and a biased crowding scheme were suggested. Thiele et al. suggest a hybrid approach which combine ideas from both evolutionary and interactive multi-objective optimization [24]. The principle is first give a rough approximation, and then generates a more accurate approximation of the area where the decision maker's most satisfactory solution lies. Deb and Kumar present an interactive methodology for finding a preferred set of solutions focused on a small non-dominated region, instead of the complete pareto-optimal frontier [4]. All the aforementioned methods have got promising results after the user preference was incorporated into the EMO algorithms.

In the paper, we introduce a non-dominated front searching algorithm based on user preference (NFSA-UP) to solve the parameter set problem of cognitive radio system. During the searching of pareto front of multi objects, the preference information is utilized to direct the evolutionary procedure. In each generation, the individuals are selected to the next generation based on the front orders and individual distances to the preference directions. The simulation results of 64 subcarriers in the CR network demonstrated that, based on the user preference, the optimal transmission parameters can be effectively found, under the predefined quality of service (QoS).

2. Problem definition

Assuming a multicarrier dynamic wireless environment with N_c subcarriers, the basic characteristic of CR is to sense the environmental parameters, and it learns itself to adjust the value of transmission parameters to achieve the predefined quality of service (QoS). In CR system, the environmental parameters act as input to the problem and the transmission parameters act as decision variables. Hence the problem can be defined as to find the set of transmission parameters by modeling the scenarios as multi-objective functions [6]. The proposed algorithm is based on user preference to solve the formulated multi-objective function to obtain the required solutions. The below subsection briefs about the radio parameters involved in CR engine.