Pervasive and Mobile Computing 22 (2015) 71–89

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

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

A quality of service distributed optimizer for Cognitive Radio Sensor Networks

Tarek M. Salem [a,*], Salah Abdel-Mageid [b], Sherine M. Abd El-kader [a], Mohamed Zaki [b]

[a] Electronics Research Institute, Computers and Systems Department, Cairo, Egypt

[b] Al-Azhar University, Computers and Systems Department, Cairo, Egypt

ARTICLE INFO

Article history:
Available online 12 June 2015

Keywords:
Cognitive Radio Sensor Networks
Multi-objective optimization
Genetic Algorithms
Non-dominated Sorting Genetic Algorithm
Simulating Annealing

ABSTRACT

In Cognitive Radio Sensor Networks (CRSNs), a sensor node is provided with a cognitive radio unit to overcome the problem of frequency spectrum being crowded. Sensor nodes sense frequency gaps for Primary Users (PUs) to work as Secondary Users (SUs). However, Quality of Service (QoS) requirements for sensor nodes such as maximizing throughput and minimizing transmission power conflicts with minimizing interference between sensor nodes and PUs. Existing works have optimized QoS parameters considering frequency interference problem using Genetic Algorithms (GA) and Simulating Annealing (SA). In this paper, a distributed optimizer for CRSNs based on advanced multi-objective evolutionary algorithms named Non-dominated Sorting Genetic Algorithm (**NSGA**-II) has been proposed. A set of accurate fitness functions for NSGA-II implementation that fully control evolution of the algorithm have been employed. To the best of our knowledge, there is no published research in **CRSN** that contains all these intrinsic fitness functions in one system model. Simulation results show that the proposed optimizer can work as a distributed solution for CRSNs because it achieves a minimum number of iterations and minimum coverage time to reach an optimal solution compared to GA and SA. Such minimization matches the energy requirement for the underlying sensor nodes.

1. Introduction

Wireless Sensor Networks (WSNs) play a very important role in many applications, such as industrial monitoring [1], environmental monitoring [2], health monitoring [3], and seismic vibration sensing. It has found applications in many *ad hoc*, military and commercial wireless systems. Due to rapid growth of WSNs in every facet of our daily lives, limited frequency spectrum available for WSN applications will be heavily crowded. Cognitive Radio (CR) is a new technology candidate for next generation of wireless communications systems to utilize frequency spectrum.

Cognitive technique is the process of knowing through perception, planning, reasoning, acting, and continuously updating and upgrading with a history of learning. CR has the ability to know unutilized spectrum in licensed and unlicensed spectrum bands such as ISM, GSM, and TV bands, and utilizes unused spectrum opportunistically [4]. PUs have the right to use the spectrum anytime, whereas SUs can exploit spectrum only when PU is idle. Recently, a CR has been used in WSNs to avoid frequency limitations imposed by conventional WSNs and enable sensor nodes to work as SUs (it is called Cognitive

* Corresponding author.
E-mail addresses: tareksalem@eri.sci.eg (T.M. Salem), smageid@azhar.edu.eg (S. Abdel-Mageid), sherine@eri.sci.eg (S.M. Abd El-kader), azhar@eun.eg (M. Zaki).

http://dx.doi.org/10.1016/j.pmcj.2015.06.002
1574-1192/

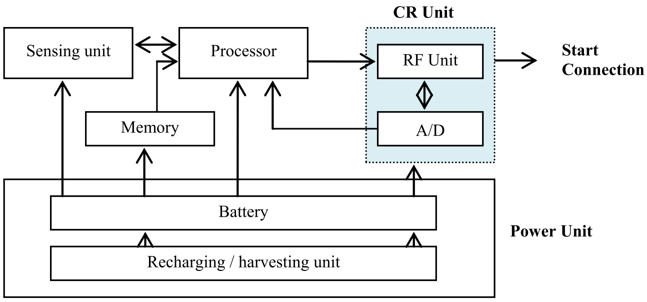

Fig. 1. Hardware structure of CRSN.

Radio Sensor Networks, CRSNs) [5]. CRSN node hardware structure is mainly composed of sensing unit, processor unit, memory unit, power unit, and CR transceiver unit as depicted in Fig. 1.

On the contrary of conventional sensor nodes, cognitive sensor nodes perform additional tasks such as spectrum decision in which the CR selects the proper spectrum band from a variety of vacant bands using an infrastructure based (e.g. Base Station) or non-infrastructure (e.g. ad hoc). Many researches have been introduced for spectrum decision [6–9]. Spectrum decision process cannot promise a sensor node with a frequency band achieving all QoS requirements due to probability of interference with PUs. Our problem is how to reach better QoS parameters for cognitive sensor nodes with minimum interference. This issue is considered a multi-objective problem.

In this paper, QoS optimizer is formulated in a multi-objective form based on advanced multi-objective evolutionary algorithm (NSGA-II) to obtain required optimal QoS parameters achieving desired goals of CRSN application and taking into account complexity time for NSGA-II. NSGA-II has been chosen because of its ability to find much better spread of solutions and better convergence near true Pareto-optimal front compared to other algorithms [10,11]. In spite of the fact that NSGA-II being a type of GA, it has different characteristics which make it fast and effective related to convergence of parameters and ability to find a suitable solution with optimal convergence of parameters. The characteristics of NSGA-II are summarized as follows [10,11]:

(1) **Computational complexity**: NSGA-II uses a fast non-dominated sorting approach instead of the original sorting algorithm of NSGA to decrease its computational complexity to $O\left(GN\log^{M-1} N\right)$, where G is number of generations, M is number of objectives, and N is population size. The computational complexity of typical NSGA-II and the basic NSGA algorithm are $O(GMN^2)$ and $O(GMN^3)$, respectively. This feature makes NSGA-II more efficient than NSGA for large population cases [11].
(2) **Elitism preservation**: Replacement with elitism methods can monotonously enhance the solution quality and speed up the performance of GAs significantly. If μ and λ are the better parents and children, respectively, NSGA-II adopts $(\mu+\lambda)$ evolution strategy to keep elitism and to prevent the loss of good solutions once they are found [10].
(3) **Parameter reduction**: Conventional sharing approach is a diversity ensuring mechanism that can get a wide variety of equivalent solutions in a population. However, a sharing parameter should be specified to set the sharing extent desired in a problem. Therefore, NSGA-II defines density estimation metric and applies the crowded comparison operator with less required parameters to keep diversity between solutions [10].
(4) **Crossover operator**: The crossover integrates a gene evaluation method with a gene-therapy approach in the traditional NSGA-II for finding uniformly distributed Pareto-optimal front of multi-objective optimization problems. For additional improvement in the advantages of fast non-dominate sorting and diversity preservation in NSGA-II, the proposed gene-evaluation method partially evaluates the merit of different crossover genes by substituting them in better parent and then calculating the fitness variances. The gene-therapy approach incorporates with the evaluative crossover to cure the mating parents mutually with respect to their gene contribution in order to retain superior genomes in the evolutionary population [11].

In fact, for each solution, NSGA-II calculates two entities: (i) the set of solutions dominated by a particular solution, and (ii) the set of dominating solutions for that particular solution. The calculations of these two entities require space complexity $O(N^2)$. Therefore, the reduction in time cost of NSGA-II is achieved on the expense of the space complexity which has been raised from O (N) for basic NSGA to $O(N^2)$ for NSGA-II. Such increase in the space complexity is due to the fact that NSGA-II algorithm preserves near optimal solutions for elitism realization.

Because of its computational attractiveness, NSGA-II has been selected to solve the coverage problem in WSNs [12–14]. Due to resources restrictions in memory and processing size in sensor node, CRSN engine needs an effective algorithm such as NSGA-II able to achieve QoS parameters with less number of generations and convergence time. Moreover, it enables us to optimize more than one objective at same time.

An important part of NSGA-II algorithm is the fitness function that guides the evolution of NSGA-II parameter set to an optimal set. Several fitness functions that are used to score how well a parameter set matches given objectives have been introduced [15–19]. These fitness functions provide numerical analysis of relationships between environmental parameters and QoS parameters. The proposed scheme represents the core controller for CRSN parameter adaptation. This