Genetic Algorithm-based Crowdsensing for Cognitive Radio Networks

Omar S. Mossad
Computer and Systems Eng. Dept.
Faculty of Engineering,
Alexandria University, Egypt
E-mail: omar.salaheldine@alexu.edu.eg

Mustafa ElNainay
Computer and Systems Eng. Dept.
Faculty of Engineering,
Alexandria University, Egypt
E-mail: ymustafa@alexu.edu.eg

***Abstract*—One of the main challenges in cognitive radios is spectrum sensing. Cooperative spectrum sensing scheme among mobile users can be used to determine the usage profile of wide spectrum bands in a large geographical region. In a large mobile crowdsensing environment, the key step is to assign the sensing task among mobile users to maximize the spectrum sensing performance while reducing the cost incurred by the mobile users during the sensing process. In this paper, we propose two genetic algorithm-based approaches to solve the NP-hard problem of spectrum sensing task assignment among mobile users. The first algorithm uses a centralized genetic algorithm scheme to maximize the spectrum sensing utility function. The second algorithm uses an island genetic algorithm to assign the sensing task among mobile users in a distributive way. Simulation results show that both algorithms achieve comparable spectrum utility measure to the one obtained by running recently proposed particle swarm optimization and greedy approximation algorithms while reducing the running time of the algorithm by a significant factor. In addition, the island algorithm massively outperforms both algorithms in the running time by running the algorithm independently at each sensing location and exchanging the necessary information for the overlapping locations, removing the bottleneck of having a central spectrum profiling unit to assign the sensing tasks among mobile users.**

***Keywords*—** cognitive radio; crowdsensing; spectrum profiling; genetic algorithm; island genetic algorithm

I. Introduction

With the current, and anticipated future, gigantic growth of wireless traffic, the necessity for dynamic spectrum access and efficient spectrum utilization arises. According to Cisco, traffic from wireless and mobile devices will account for more than 63 percent of total IP traffic by 2021 [1]. The research conducted by the spectrum sharing company on the spectrum utilization in the frequency bands ranging from 30MHz to 3000MHz in the US city of Chicago showed that the average utilization rate of the frequency band was only 17.4% or less [2]. A similar research on multiple European cities showed a lower utilization rate of 10.7% [3].

Cognitive radio (CR) has recently attracted a significant attention as a promising technology to overcome the spectrum under-utilization problem caused by the current inflexible spectrum allocation policy [4]. In CR networks, unlicensed secondary users (SUs) should sense the radio environment, and adaptively change the transmission parameters to avoid the interference to licensed primary users (PUs) [5]. To overcome the various factors that can affect the spectrum sensing performance, cooperative spectrum sensing can be applied by exchanging the sensing results among all SUs that participate in the sensing process [6]. In [7] a variety of fusion rules were studied to provide an accurate global decision. In a crowdsensing environment, it is necessary to find the optimal task allocation among sensing nodes. This is challenging since the quality of the sensing tasks are typically associated with specific locations and mobile users present in each location are constrained by time and energy budgets [8]. The contributions of this paper are: introducing a centralized genetic algorithm (GA) approach to solve the problem of sensing task assignment among mobile users to maximize the spectrum utility while maintaining a time and budget constraint, introducing an island GA based approach that benefits from the separability of the problem to maximize the concurrent GA runs in order to reduce the total running time and a quantitative evaluation to highlight the advantages and performance of the algorithms.

The remainder of the paper is organized as follows. A survey of the related work is presented in Section II. The system model is described in Section III. The proposed centralized GA-based algorithm is presented in Section IV. The distributed island GA algorithm is described in Section V. The evaluation of our work is presented in Section VI. Section VII concludes the paper and discusses potential future work.

II. Related Work

Cooperative spectrum sensing has been a major research topic and multiple publications have tackled various techniques to improve the sensing performance. Among the efforts done are [9]–[11] where the authors try to find optimal solutions for spectrum monitoring. Channel assignment in spectrum sensing was studied in [12] and three different algorithms were proposed to solve this problem. In order to decrease the sensing time, [13] proposed a sensing task assignment scheme based on the Hungarian algorithm that leads to the reduction of the probability of misdetection and the probability of false alarm. A fuzzy inference based scheme for distributing the sensing task among cognitive nodes was proposed in [14] in order to reduce the overall probability of sensing error. A distributed scheme to assign spectrum

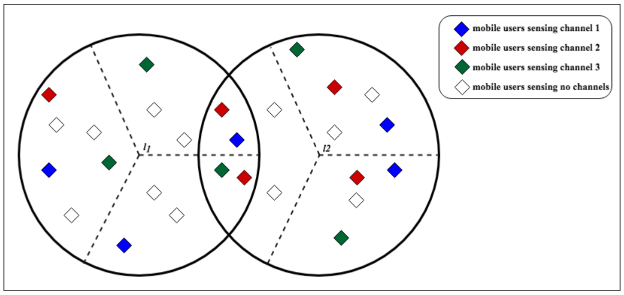

Fig. 1. System Model

sensing task to mobile users was introduced in [15] where four algorithms based on transition probabilities were used to maximize the spectrum sensing performance. The approach in [10] introduces the idea of a budget constraint by considering that mobile users incur a cost that the fusion center must compensate. The model used in [16] describes the mobile crowdsensing environment and formulates the task assignment problem providing a near optimal solution.

Shin et al. [17] focused on the task assignment problem in a large crowdsensing environment while assuming the presence of a Crowdsourcing-based Spectrum-profiling Service Provider (CSSP). They proved that such problem is NP-hard and provided two different algorithms to solve it. Both the greedy and Linear Program (LP) rounding algorithms achieved similar performance in terms of spectrum utility with some improvements in the running time. The main observation to be made on this effort is that it did not consider the locations overlaps as a factor that may affect the utility function. In [18] Zhai and Wang modelled the sensing task assignment problem as a maximum coverage problem which is NP-hard and tried to solve the problem using a particle swarm optimization (PSO) approach. However, it can be argued that PSO is usually used to solve problems with continuous domains whereas the task assignment problem has a discrete domain.

According to [19], evolutionary algorithm such as genetic algorithm can be used to solve NP-hard problems, specifically how to schedule and assign tasks to multiple users. Additionally [20] proposed a new scheme for GA where the algorithm can run distributively at independent islands. To obtain the global solution, migration occurs between the different islands to exchange their best individuals. Whitley et. al. [21] argued that island GA can be used to solve linearly separable problems by applying a parallel approach to reduce running time and solve problems with infinite population. Inspired by the effectiveness of GA and island GA, we considered using them to solve the crowdsensing task assignment problem as highlighted in the next sections.

III. System Model

Following the models proposed in [17] and [18], our system is shown in Fig. 1. We consider a model with multiple locations of interest within which mobile users will perform the sensing tasks to determine the empty spectrum bands. Each target location $l_i \, \epsilon \, L = \{l_1, l_2, \cdots, l_{|L|}\}$ is divided into a number of circular sectors centered around l_i, called sub-locations $s_{i,j}$ where $i \, \epsilon \, \{1, 2, \cdots, |L|\}$ and $j \, \epsilon \, \{1, 2, \cdots, |S|\}$, $|S|$ is the number of sub-locations in each location. A number of mobile users $U = \{u_1, u_2, \cdots, u_{|U|}\}$ are present in all sub-locations and are responsible for spectrum sensing over a number of bands $B = \{b_1, b_2, \cdots, b_{|B|}\}$ where $|B|$ is the number of spectrum bands available in the system. For large spectrum profiling, we consider wide frequency bands to cover the entire spectrum. Each mobile user u_k is allowed to sense a single band and will incur a cost c_k that depends on the reward being paid to him for participating in the sensing process independent of the band he was assigned. The cost simulates the lower performance incurred by the user for forfeiting one of his antennas to perform a sensing task instead of normal transmission. In the case of centralized genetic algorithm, we assume a Crowdsourcing-based Spectrum-profiling Service Provider (CSSP) is present similar to the approach in [17] and is responsible for the assignment of the sensing tasks among mobile users.

We formulate the crowdsensing task assignment problem as follows. For each mobile user u_k, we define B binary variables $x_{k,b} \, \epsilon \, \{0, 1\}$, where $k = \{1, 2, \cdots, |U|\}$ and $b = \{1, 2, \cdots, |B|\}$, $x_{k,b} = 1$ indicates that user u_k is sensing band b. Since each mobile user can sense a single band, we have the following constraint:

$$\sum_{b \epsilon [|B|]} x_{k,b} \leq 1 \quad \forall \, k \, \epsilon \, [|U|] \tag{1}$$

Additionally, we assume that there is a maximum cost C that depends on the CSSP budget. In this case, we have:

$$\sum_{k \epsilon [|U|]} c_k . \sum_{b \epsilon [|B|]} x_{k,b} \leq C \tag{2}$$

To define the spectrum utility function, we consider that a location is covered if all the bands are covered by at least one mobile user in each and every one of its sub-locations. Therefore, we introduce the following variable $y_{s_{ij},b} \, \epsilon \, \{0, 1\}$, where $y_{s_{ij},b} = 1$ indicates that spectrum band b is covered in sub-location $s_{i,j}$ by at least one mobile user and $y_{s_{ij},b} = 0$ indicates that no mobile user is sensing the spectrum band b in sub-location $s_{i,j}$. Thus, we have

$$y_{s_{ij},b} = min \left\{ 1, \sum_{u' \epsilon [U'_s]} x_{u',b} \right\} \tag{3}$$

where U'_s is the set of mobile users present in sub-location s. Considering that each location has S sub-locations, we can determine the band coverage in a location

$$q_{i,b} = \sum_{s' \epsilon [|S|]} y_{s_{i,s'},b} \tag{4}$$

To map the location coverage to a value in the range [0,1], we will use $f_{i,b} : \{0, 1, \cdots, |S|\} \rightarrow [0, 1]$. Thus, we have $f_{i,b}(0) = 0$ if the band b is not covered in any of the sub-locations of location i and $f_{i,b}(|S|) = 1$ if the band b is covered in all the sub-locations of location i. If a certain band is partially covered in a certain location, then $f_{i,b}$ will have a value between 0 and 1. It is clear that $f_{i,b}$ must satisfy the condition that covering more locations even partially is always better than covering an entire location solely, thus it is a non-decreasing function satisfying the property of diminishing returns. To differentiate between the importance of each location and each band, we define a weight $w_{i,b}$ for each $i \epsilon \{1, 2, \cdots, |L|\}$ and $b \ \epsilon \{1, 2, \cdots, |B|\}$. The overall spectrum utility function is defined as:

$$Spectrum\_Utility = \sum_{i\epsilon[|L|]} \sum_{b\epsilon[|B|]} w_{i,b} \ f_{i,b}(q_{i,b}) \quad (5)$$

The crowdsensing task assignment problem can be described as a constrained maximization problem where the main goal is to maximize the value of the spectrum utility function while the total cost incurred by mobile users sensing a single spectrum band is kept below the system budget i.e.

$$maximize \sum_{i\epsilon[|L|]} \sum_{b\epsilon[|B|]} w_{i,b} \ f_{i,b}(q_{i,b}) \quad (6)$$
$$Subject\ to\ equations\ (1)\ and\ (2)$$

IV. Centralized Genetic Algorithm

We propose a genetic algorithm-based approach that solves the problem of maximizing the spectrum utility function. The details of the algorithm are described in the following subsections.

A. Chromosome Structure

Each chromosome consists of U genes, each gene represents a particular user sensing a single band, where $|U|$ is the number of mobile users in the system. Each gene consists of one field. This field represents the spectrum band that the user will be assigned to sense and zero if the user will not participate in the sensing process. For example, in Table I, u_1 and u_2 will sense channels b_1 and b_2 respectively, while u_U will not participate in the sensing process and hence will not incur any costs.

B. Initialization

A population of chromosomes is initialized with random values $g \ \epsilon \{0, 1, 2, \cdots, |B|\}$ for each gene in every chromosome.

C. Genetic Operations

The two primary genetic operations, mutation and crossover, are applied to chromosomes randomly with probabilities p_m and p_c respectively.

1) Mutation: The mutation operator helps ensure that the search does not stuck in a local optimum. A chromosome is mutated by replacing its genes, with probability p_m. A chosen gene (user u_i for example) sensing band b_j or not sensing at all is replaced with another band or none randomly.

TABLE I
Chromosome Structure

u_1	u_2	$\cdots$	u_U
b_1	b_2	$\cdots$	0

2) Crossover: The crossover operator is responsible for fine tuning the search in region of interests through mating pairs of chromosomes producing new ones. A single-point crossover between chromosome pairs is applied to every chromosome with probability p_c.

D. Selection

Selection is the stage of a genetic algorithm in which individual chromosomes are chosen from a population for later breeding. A fitness function is evaluated for each chromosome. Each chromosome of the current generation enters a tournament with another chromosome drawn randomly from the same population, then the fittest (highest value in the fitness function) of the chromosomes is selected. This selection process generates 90% of the population used in the next generation. The remaining 10% of the population are generated by the elitism. Elitism involves copying a small proportion of the fittest candidates, unchanged, into the next generation. This can sometimes have an impact on the performance by ensuring that the evolutionary algorithm does not waste time re-discovering previously discarded partial solutions. Candidate solutions that are preserved unchanged through elitism remain eligible for selection as parents when breeding for the remainder of the next generation. The fitness function shown in eq. (7) represents an unconstrained optimization problem reflecting the total number of bands sensed by the mobile users and the penalties resulting from the total cost surpassing the maximum allowed budget at the CSSP.

$$Fitness = Spectrum\_Utility + Penalty \quad (7)$$

The genetic algorithm tries to find the chromosome which maximizes the fitness function. The penalty is used to prevent the chromosomes from exceeding their budget and violating the constraints. Therefore, we can describe the fitness function as follows, given the total cost incurred by all mobile nodes

$$Tc = \sum_{k\epsilon[|U|]} c_k. \sum_{b\epsilon[|B|]} x_{k,b} \quad (8)$$

$$Fitness = \begin{cases} 0 & Tc > C, \\ Spectrum\_Utility & Tc \leq C \end{cases} \quad (9)$$

The fitness function in eq. (9) indicates that if the total costs of a certain chromosome exceeds the allocated budget, its fitness will be equal to zero. Therefore, the budget constraint can not be violated.

E. Termination

The algorithm is terminated when a maximum number of generations is reached or when no significant relative change in the fitness over a predefined number of stall generations

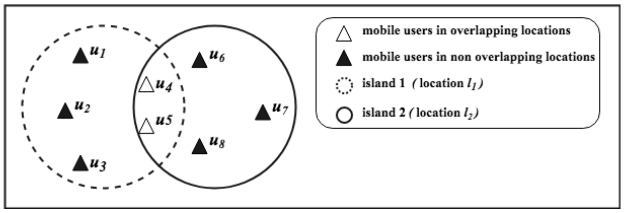

Fig. 2. System with two overlapping locations

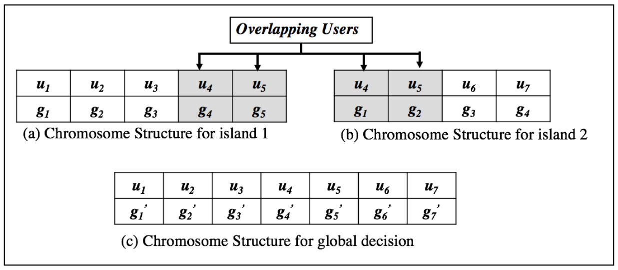

Fig. 3. Chromosome Structure for Island GA

happens. After termination, the solution with the highest fitness function is then determined and chosen.

V. Island Genetic Algorithm

In this section, we propose another version of the genetic algorithm which uses an island model similar to the approach in [21]. This model assumes that each location constitute an isolated island with its own independent mobile users responsible for the sensing tasks as shown in Fig. 2. A genetic algorithm similar to the previous section, is performed within each isolated island, in order to obtain the best sensing task assignment among mobile users located inside this island. The presence of mobile users in overlapping locations can create a conflict between each island solution. For example, Fig. 3 represents the chromosome structure of the most fit individuals for the scenario in Fig. 2 where locations l_1 and l_2 are modelled as two separate islands. The genes g_4 and g_5 in the first chromosome describe the best sensing task assignment in the first island for users u_4 and u_5 respectively. These users are present in the second island as well and are described by genes g_1 and g_2 in the second chromosome with different band assigned. Therefore, a series of migrations occur between the two locations in which they exchange their best assignment for the overlapping users (u_4 and u_5) until they achieve an agreement to produce a unified global decision.

The details of the algorithm are described in the following subsections.

A. Initial Setup

During the initial setup phase, each location communicates with the neighbouring locations to determine if they have any overlapping mobile users. The algorithm begins by dividing the entire system into isolated sub-systems $M = \left\{m_1, m_2, \cdots, m_{|M|}\right\}$ composed of locations with overlapping users as shown in Fig. 4. Next, the island genetic algorithm is

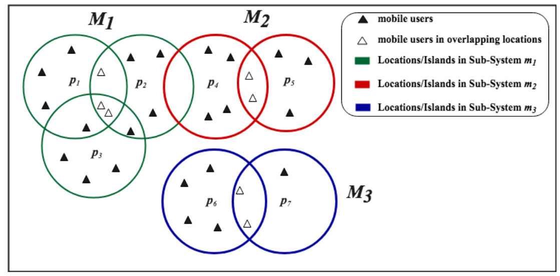

Fig. 4. Sub-Systems obtained during the Initial Setup Phase

performed to generate the best individuals for each sub-system independently. Let F be a function that uses the genetic algorithm to assign sensing tasks among mobile users and returns the best individual, we have

$$F(M) = G(m_1) + G(m_2) + \cdots + G\left(m_{|M|}\right), \qquad (10)$$

where $G(m_1)$ is a genetic algorithm run using the mobile users present in sub-system m_1. Thus, we divide the main problem into a group of sub-problems. For simplification, we consider a single sub-system in the next sections.

B. Genetic Algorithm

The island genetic algorithm starts by applying a genetic algorithm run on each one of its islands $p_i \epsilon P = \left\{p_1, p_2, \cdots, p_{|P|}\right\}$ to produce the best sensing task assignment for each island separately. The number of islands $|P|$ is equal to the number of locations $|L|$ in the system.
Next, a migration stage occurs where each island exchanges necessary information with the neighbouring islands. The information being shared can be summarized as:

- The best sensing task assignment for overlapping mobile users drawn from the best 10% of the population.
- The maximum fitness value obtained when using the previous assignment of the overlapping mobile users.

The main idea of the migration step is to force the other islands to generate new individuals having the same assignment for overlapping users.
A series of genetic algorithm runs followed by the migration step are performed until one of the following conditions is met:

- The islands have agreed on the sensing task assignment for the overlapping mobile users based on the maximum sum of individual islands finesses.
- A maximum number of migrations N_m is achieved. In this case, the assignment that produced the maximum sum of individual islands finesses is selected.

The island genetic algorithm cycle is shown in Fig. 5.

The main challenge in the island model is how to apply the global constraints on each separate island. In our case, the budget constraint was defined by the CSSP and the total cost incurred by mobile users should not exceed the budget C. Therefore, we propose a constraint relaxation approach to handle this challenge as follows.

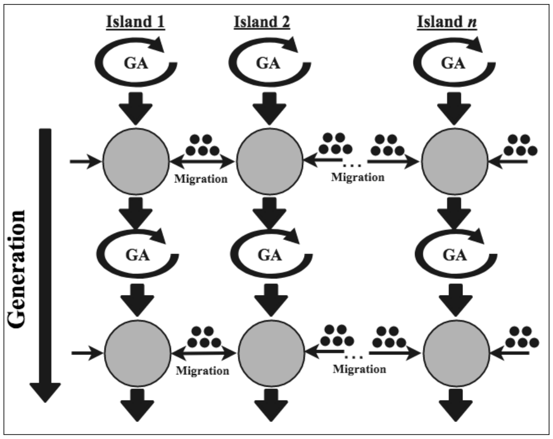

Fig. 5. Island Genetic Algorithm Cycle

We define the variable $z_{k,p}\ \epsilon\ \{0,1\}$, where $k = \{1,2,\cdots,|U|\}$ and $p = \{1,2,\cdots,|P|\}$, $z_{k,p} = 1$ indicates that user u_k is present in island p. Since each mobile user can exist in zero or more islands, we will use r_k to describe the number of islands where user u_k is located

$$r_k = \sum_{p\epsilon[|P|]} z_{k,p} \tag{11}$$

Since a mobile user present in multiple islands incurs the same cost if he participates in the sensing, we will use a normalized cost function

$$c'_k = \begin{cases} 0 & r_k = 0, \\ \frac{1}{r_k} & r_k > 0 \end{cases} \tag{12}$$

We can then assume that the maximum cost that can be incurred within an island due to mobile users participating in the sensing process can be described by:

$$C\left(p\right) = \frac{C}{\sum_{k=1}^{|U|} c_k} \cdot \sum_{k\epsilon[|U|]} c'_k \cdot z_{k,p} \tag{13}$$
$$where\, p\, \epsilon \, \{1,2,\cdots,|P|\}$$

Then, the total cost within each island can be calculated using:

$$Tc\left(p\right) = \sum_{k\epsilon[|U|]} c'_k \cdot z_{k,p} \cdot \sum_{b\epsilon[|B|]} x_{k,b} \tag{14}$$
$$where\, p\, \epsilon \, \{1,2,\cdots,|P|\}$$

The genetic algorithm fitness function for each island can then be described as an unconstrained optimization using eq. (7), with the penalties being described as:

$$Penalty(p) \; = \; min(\, 0, \; C(p) - Tc(p) \,) \tag{15}$$

According to eq. (15), the penalty value will increase depending on the amount by which the total cost, incurred by mobile users in a certain island, exceeds its acceptable budget.

TABLE II
SIMULATION PARAMETERS

Parameter	Distribution/Value
Area	100 m^2
Radius	0.8 m
Number of Locations L	$\{30,35,40,45,50\}$
Number of Users U	$\{100,120,140,160,180,200\}$
Number of Freq. Bands B	3
Number of Sub-locations S	3
Location-Band Weights $w_{i,b}$	$\sim$ U $(1,3)$
User Cost c_k	$\sim$ U $(1,5)$
CSSP Budget C	$0.6\times\sum_{k=1}^{\lvert U\rvert} c_k$
$f_{i,b}(m)\;\; m\,\epsilon\,\{0,1,2,3\}$	[0, 0.6, 0.85, 1]

TABLE III
GENETIC ALGORITHMS PARAMETERS

Parameter	Centralized GA	Island GA
Number of Generations	500	200
Population Size	60	50
Probability of Mutation P_m	0.3	0.3
Probability of Crossover P_c	0.2	0.2

C. Termination

At the end, each sub-system exchanges his best assignment for the mobile users with the neighboring sub-systems. The new individual obtained from this step describes the best global solution for the entire system

D. Discussion

It is clear that such algorithm runs in a distributive matter where each island is modelled as a separable problem. The main advantages of this approach are the great reduction in the running time and the possibility to operate on extremely large populations. On the other hand, a minor overhead occurs due to the simple communication between these islands during the migration and cost calculation phases. Also, the cost relaxation previously discussed can lead to lower spectrum utility values since some mobile users may be prevented from sensing due to the island budget constraint while the global budget constraint is not violated.

VI. NUMERICAL RESULTS

We evaluate the system performance using Python and DEAP framework [22]. The simulation parameters are described in Table II and the genetic algorithms parameters are described in Table III. Since the centralized GA operates on the entire number of mobile users, we will use a population of size 60 and the number of generations is 500 to allow a considerable number of mutations and crossovers. The island GA operates only on the mobile users in each island, so the population size is smaller at 50 while the number of generations used is 200.

First, we evaluate the spectrum utility obtained by both genetic algorithms compared to the greedy algorithm of [17]

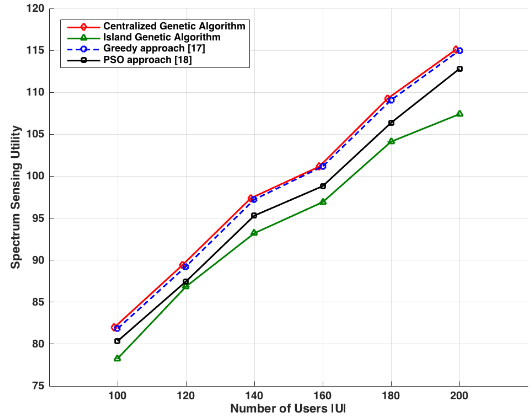

Fig. 6. Spectrum Utility, Number of Locations = 40

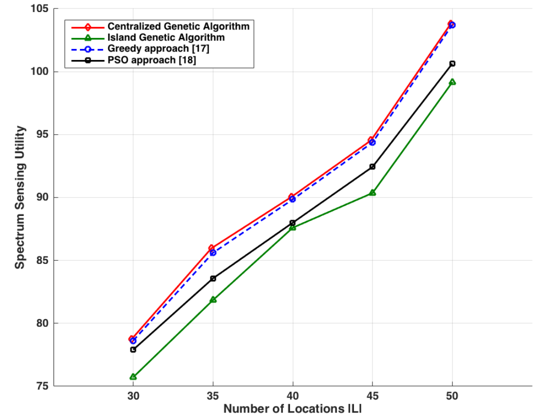

Fig. 7. Spectrum Utility, Number of Users = 120

and the particle swarm optimization algorithm of [18] with a swarm size of 300 and a particle lifetime of 70, when varying the number of users in the system while keeping the number of locations fixed at 40. The results are depicted in Fig. 6. The results demonstrate that the greedy and centralized GA achieve similar spectrum utility that is higher than the PSO, while the island GA has smaller spectrum utility values as a result of the cost relaxation process. Next, we perform the same comparison when the number of mobile users is fixed at 120 users, while the number of locations varies as in Fig. 7. Similar to the previous results, the island GA has lower spectrum utility values than both the greedy and the centralized GA, but its values become comparable to the PSO.

Finally, we consider the running time for all algorithms as shown in Fig. 8. The results demonstrate that the island GA runs much faster than the centralized version while the PSO and greedy approaches lag behind despite producing similar spectrum utility values. In Fig. 8, there is a massive reduction in the running time of the island GA and the difference intensifies as the number of users increases. This demonstrates the advantages of applying a distributive approach since in the case of island GA the number of generations and population sizes used are much less than the centralized version to obtain similar results. The running time of the island GA includes the time for the migration phase. The minor decrease in the spectrum utility in the case of island GA is due to the relaxation factor we applied to the total cost. Hence, the total cost might have not been exceeded while some users were prevented from the participation in the sensing task to satisfy the island budget constraint. This reduction is justified by the considerable reduction in the running time of the algorithm.

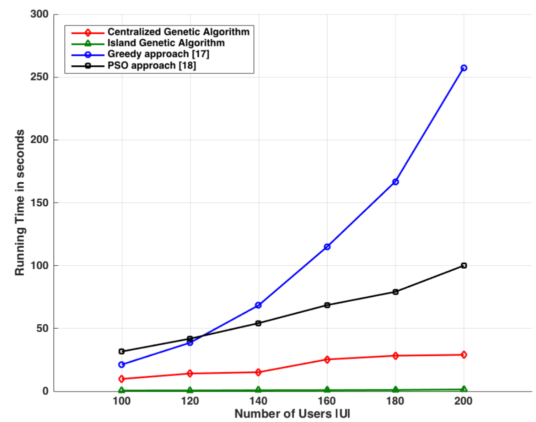

Fig. 8. Running-Time, Number of Locations = 40

VII. Conclusion and Future Work

In this paper, we proposed two different metaheuristic algorithms for solving the NP-hard problem of spectrum sensing task assignment in a large crowdsensing environment. Both algorithms are based on the genetic algorithm and operate in a centralized and distributed manners respectively. Simulation results show that both algorithms provided comparable results to the previously proposed particle swarm optimization and greedy approaches in terms of the spectrum utility measure, while the island genetic algorithm outperforms both algorithms in terms of running time due to the distributive manner. As a future work, the system can be extended to handle users mobility and assign the sensing tasks in a dynamic environment. Also, a study on the genetic algorithm parameters and their effect on the system performance can be provided.

References

[1] C. W. Paper, “Cisco visual networking index: Global mobile data traffic forecast update, 2016-2021,” 2017.

[2] M. A. McHenry, P. A. Tenhula, D. McCloskey, D. A. Roberson, and C. S. Hood, “Chicago spectrum occupancy measurements & analysis and a long-term studies proposal,” in *Proceedings of the first international workshop on Technology and policy for accessing spectrum - TAPAS 06*. ACM Press, 2006.

[3] V. Valenta, R. Maršálek, G. Baudoin, M. Villegas, M. Suarez, and F. Robert, “Survey on spectrum utilization in europe: Measurements, analyses and observations,” in *Proceedings of the 5th International ICST Conference on Cognitive Radio Oriented Wireless Networks and Communications*. IEEE, 2010.

[4] J. Mitola and G. Maguire, "Cognitive radio: making software radios more personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13–18, 1999.

[5] K.-C. Chen and R. Prasad, *Spectrum Sensing*. John Wiley Sons, Ltd, 2009, pp. 183–229.

[6] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical Communication*, vol. 4, no. 1, pp. 40–62, mar 2011.

[7] R. Bouraoui and H. Besbes, "Cooperative spectrum sensing for cognitive radio networks: Fusion rules performance analysis," in *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, sep 2016.

[8] S. He, D.-H. Shin, J. Zhang, and J. Chen, "Toward optimal allocation of location dependent tasks in crowdsensing," in *IEEE INFOCOM 2014 - IEEE Conference on Computer Communications*. IEEE, apr 2014.

[9] J. Peng, Y. Zhu, Q. Zhao, H. Zhu, J. Cao, G. Xue, and B. Li, "Fair energy-efficient sensing task allocation in participatory sensing with smartphones," *The Computer Journal*, vol. 60, no. 6, pp. 850–865, feb 2017.

[10] S. He, D.-H. Shin, J. Zhang, and J. Chen, "Toward optimal allocation of location dependent tasks in crowdsensing," in *IEEE INFOCOM 2014 - IEEE Conference on Computer Communications*. IEEE, apr 2014.

[11] D.-H. Shin and S. Bagchi, "An optimization framework for monitoring multi-channel multi-radio wireless mesh networks," *Ad Hoc Networks*, vol. 11, no. 3, pp. 926–943, may 2013.

[12] W. Wang, B. Kasiri, J. Cai, and A. S. Alfa, "Channel assignment schemes for cooperative spectrum sensing in multi-channel cognitive radio networks," *Wireless Communications and Mobile Computing*, vol. 15, no. 10, pp. 1471–1484, oct 2013.

[13] M. Nabil, W. El-Sayed, and M. ElNainay, "A cooperative spectrum sensing scheme based on task assignment algorithm for cognitive radio networks," in *2014 International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, aug 2014.

[14] M. Nabil and M. ElNainay, "Fuzzy-based assignment algorithm for channel sensing task in cognitive radio networks," in *2016 IEEE Symposium on Computers and Communication (ISCC)*. IEEE, jun 2016.

[15] L. Zhai, H. Wang, and C. Liu, "Distributed schemes for crowdsourcing-based sensing task assignment in cognitive radio networks," *Wireless Communications and Mobile Computing*, vol. 2017, pp. 1–8, 2017.

[16] Z. Shi, H. Huang, Y.-E. Sun, X. Wu, F. Li, and M. Tian, "An efficient task assignment mechanism for crowdsensing systems," in *Cloud Computing and Security*. Springer International Publishing, 2016, pp. 14–24.

[17] D.-H. Shin, S. He, and J. Zhang, "Joint sensing task and subband allocation for large-scale spectrum profiling," in *2015 IEEE Conference on Computer Communications (INFOCOM)*. IEEE, apr 2015.

[18] L. Zhai and H. Wang, "Crowdsensing task assignment based on particle swarm optimization in cognitive radio networks," *Wireless Communications and Mobile Computing*, vol. 2017, pp. 1–9, 2017.

[19] A. Diveev and O. Bobr, "Variational genetic algorithm for np-hard scheduling problem solution," *Procedia Computer Science*, vol. 103, pp. 52 – 58, 2017, xII International Symposium Intelligent Systems 2016, INTELS 2016, 5-7 October 2016, Moscow, Russia.

[20] H. Yong, "Optimal population size for partheno-genetic algorithm," in *2007 Chinese Control Conference*. IEEE, jul 2006.

[21] D. Whitley, S. Rana, and R. B. Heckendorn, "Island model genetic algorithms and linearly separable problems," in *Evolutionary Computing*. Springer Berlin Heidelberg, 1997, pp. 109–125.

[22] F.-M. D. Rainville, F.-A. Fortin, M.-A. Gardner, M. Parizeau, and C. Gagné, "DEAP," in *Proceedings of the fourteenth international conference on Genetic and evolutionary computation conference companion - GECCO Companion 12*. ACM Press, 2012.