Evolutionary Search for Energy-Efficient Distributed Cooperative Spectrum Sensing

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***Abstract*—This paper concerns the energy efficiency optimization for distributed cooperative spectrum sensing. In the considered distributed spectrum sensing system, each sensor measures the local test statistic for the target spectrum bands and these measurements will be combined together through a weighted consensus protocol. In this way, all the sensors are able to make contributions to the improvement of the spectrum sensing performance. However, the significance of a sensor's contribution depends on its local signal to noise ratio. From energy efficiency perspective, it is not reasonable to invest energy on the sensors that bring little benefits. In this paper, we formulate an energy efficiency optimization framework for distributed spectrum sensing. Our objective is to achieve the target spectrum sensing performance with as few sensors as possible. Accordingly, a genetic algorithm based approach and a particle swarm optimization based approach are proposed for this problem.**

I. INTRODUCTION

In contrast to the traditional static spectrum management policy, a cognitive radio system is able to dynamically allocate the available spectrum resource [1]. Generally, in a cognitive radio system, spectrum bands are continuously detected and once a spectrum band is left idle, it will be assigned to the user in need. It is evident that an accurate detection procedure, also known as spectrum sensing, is essential for a cognitive radio system [2]. When implementing spectrum sensing with a single sensor, the performance can be critically degraded in shadowing or multipath fading environments. Accordingly, cooperative spectrum sensing is proposed to improve the sensing accuracy by exploiting the spatial diversity of multiple distributed sensors [3]. In a cooperative spectrum sensing system, the measurements from multiple sensors will be combined together to make the final detection decision. The data combination can be achieved in either a centralized or a distributed way. With centralized cooperative spectrum sensing, all the sensors deliver the data to a common fusion center, where the data will be combined for the detection. Instead, the data fusion of distributed cooperative spectrum sensing is accomplished locally by utilizing a distributed consensus algorithm [4], [5].

In a cognitive radio system, spectrum sensing should be implemented continuously to provide a real-time spectrum map. Thus, the energy consumption can be significant, especially for cooperative spectrum sensing methods, which involve a number of sensors. Therefore, energy efficiency optimization deserves serious consideration for a cooperative spectrum sensing system. The energy efficiency optimization for cooperative spectrum sensing can be formulated by a combinatorial optimization problem [6]–[8], which aims to achieve the target spectrum sensing performance by activating as few sensors as possible. Several algorithms have been proposed for the fusion center based cooperative sensing schemes. However, due to the difference of collaboration mechanism, these methods can not be applied to the distributed counterpart.

In our previous work, an energy efficiency optimization framework for distributed cooperative spectrum sensing has been proposed [9]. The considered cooperative sensors are identical and experience different signal to noise ratios (SNRs). Our objective is to find an effective sensor set with minimum size, which not only has an effective topology for the distributed sensing algorithm but also satisfies the target detection performance. We obtain the effective sensor set through a sequential sensor selection process, and a deep reinforcement learning based sensor selection policy is proposed [9]. However, the deep learning approach requires a large amount of training samples as well as a compute-intensive training process. Therefore, for the case where the training resources are not enough, alternative approaches are necessary. In this paper, two evolutionary algorithm based optimization methods, *i.e.,* generic algorithm(GA) [10] and particle swarm optimization (PSO) [11], are proposed to directly search the energy-efficient distributed spectrum sensing scheme. These two methods do not need a training process as their reinforcement learning counterpart.

II. PROBLEM FORMULATION

We consider a sensor-aided cognitive radio network which is depicted in Fig.1. Spectrum bands are assigned to the primary users (PUs) while the secondary users (SUs) are also allowed to access the spectrum bands only if they are not occupied by the PUs. A spectrum sensing network with N sensors is built to detect the states of the spectrum bands and to allocate the available spectrum to the SUs. For the spectrum

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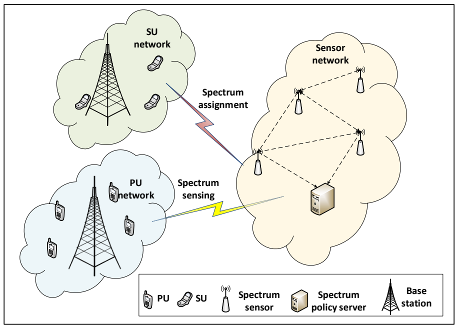


Fig. 1. A sensor-aided cognitive radio network

sensing purpose, sensor i collects data on the target spectrum band, which is

$$x_i(k) = \begin{cases} v_i(k) & \mathrm{H}_0 \\ h_i s(k) + v_i(k) & \mathrm{H}_1 \end{cases} \tag{1}$$

In this equation, H_0 and H_1 respectively represent the hypotheses of PU signal being absent or present; $s(k)$ is the signal of the PU; h_i is the channel gain from the PU transmitter to sensor i; and $v_i(k)$ is the zero-mean additive white Gaussian noise with variance being σ_i^2. The sensors are spatially distributed, and each sensor can exchange information with its neighbors. The communication relationship of the sensor network can be described by a undirected graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$. $\mathcal{V} = \{v_i\}_{i=1}^N$ is the vertex set with v_i representing the i-th sensor. $\mathcal{E} \in \mathcal{V} \times \mathcal{V}$ is the edge set, and the edge (v_i, v_j) exists only if sensor i and sensor j can communicate with each other. The neighboring vertices of v_i compose the set $\mathcal{J}_i$ in which (v_i, v_j) exists for $\forall v_j \in \mathcal{J}_i$. We assume that the energy detection based distributed spectrum sensing algorithm [5] is applied for this sensor network. With this algorithm, the sensor network obtain a sensing result through three steps. First, each sensor i measures the test statistic over M consecutive samples on the target spectrum band, which is $y_i = \sum_{k=0}^{M-1} |x_i(k)|^2$. Then, the sensors update their measurements iteratively with the following weighted consensus protocol [5]:

$$y_i(t+1) = y_i(t) + \frac{\alpha}{\delta_i} \sum_{v_j \in \mathcal{N}_i} (y_j(t) - y_i(t)), \tag{2}$$

where t is the iteration number; α is the iteration step size; and δ_i is the weighting ratio. δ_i is designed according to the channel condition of the sensor, which will be elaborated later. It has been proved that the test statistic of each sensor will converge to a common value, which is $y_c = \sum_{i=1}^N \delta_i y_i(0) / \sum_{i=1}^N \delta_i$. Clearly, y_c is the weighted average of the initial measurements of all sensors with $w_i = \delta_i / \sum_{i=1}^N \delta_i$ being the weight of the i-th sensor. Finally, y_c is delivered to the spectrum server by the neighboring sensors, and the target spectrum band will be claimed to be idle if y_c is less than a predetermined threshold γ; otherwise, the spectrum band is deemed as occupied.

According to the central limit theorem, y_i asymptotically follows the normal distribution if M is large enough. Defining the transmitted signal energy of the PU and the local SNR of sensor i by $E_s = \sum_{k=0}^{M-1} |s(k)|^2$ and $\eta_i = E_s |h_i|^2 / \sigma_i^2$, the mean and the variance of y_i can be expressed by

$$\mathrm{E}(y_i) = \begin{cases} M\sigma_i^2 & H_0 \\ (M + \eta_i)\sigma_i^2 & H_1, \end{cases} \tag{3}$$

$$\mathrm{Var}(y_i) = \begin{cases} 2M\sigma_i^4 & H_0 \\ 2(M + 2\eta_i)\sigma_i^4 & H_1. \end{cases} \tag{4}$$

Since $\{y_i\}_{i=1}^N$ are independent normal random variables, y_c are also normally distibuted with mean

$$\mathrm{E}(y_c) = \begin{cases} M\boldsymbol{\sigma}^{\mathrm{T}}\mathbf{w} & H_0 \\ (M\boldsymbol{\sigma} + E_s\mathbf{g})^{\mathrm{T}}\mathbf{w} & H_1 \end{cases} \tag{5}$$

and variance

$$\mathrm{Var}(y_c) = \begin{cases} \mathbf{w}^{\mathrm{T}}\boldsymbol{\Sigma}_{H_0}\mathbf{w} & H_0 \\ \mathbf{w}^{\mathrm{T}}\boldsymbol{\Sigma}_{H_1}\mathbf{w} & H_1 \end{cases} \tag{6}$$

where $\boldsymbol{\sigma} = [\sigma_1^2, \ \sigma_2^2, \ \ldots, \ \sigma_N^2]^{\mathrm{T}}$, $\mathbf{w} = [w_1, w_2, \ \ldots, \ w_N]^{\mathrm{T}}$, $\mathbf{g} = [|h_1|^2, |h_2|^2, \ \ldots, \ |h_N|^2]^{\mathrm{T}}$, $\boldsymbol{\Sigma}_{H_0} = 2M\mathrm{diag}^2(\boldsymbol{\sigma})$, and $\boldsymbol{\Sigma}_{H_1} = 2M\mathrm{diag}^2(\boldsymbol{\sigma}) + 4E_s\mathrm{diag}(\mathbf{g})\mathrm{diag}(\boldsymbol{\sigma})$. With this y_c, the performance of the sensor network can be analytically solved by

$$P_d = Q\left(\frac{Q^{-1}(P_{fa})\sqrt{\mathbf{w}^T\boldsymbol{\Sigma}_{H_0}\mathbf{w}} - E_s\mathbf{g}^T\mathbf{w}}{\sqrt{\mathbf{w}^T\boldsymbol{\Sigma}_{H_1}\mathbf{w}}}\right), \tag{7}$$

where $Q(\cdot)$ is the complementary cumulative distribution function of a variable that follows the normal distribution with zero mean and unit variance. For a certain P_{fa}, the optimal weights design can be found by maximizing P_d. However, the accurate analytic solution is of high mathematical complexity. By defining the deflection coefficient as

$$d^2(\mathbf{w}) = \frac{[E(y_c|H_1) - E(y_c|H_0)]^2}{\mathrm{Var}(y_c|H_0)} = \frac{(E_s\mathbf{g}^T\mathbf{w})^2}{\mathbf{w}^{\mathrm{T}}\boldsymbol{\Sigma}_{H_0}\mathbf{w}}, \tag{8}$$

an alternative near optimal weights design is discovered by maximizing $d^2(w)$ [5], [12]. The rationale behind this approach is that for a given P_{fa}, a large $d^2(\mathbf{w})$ will lead to a high P_d when the sensors are under a low SNR channel condition. By maximizing $d^2(\mathbf{w})$ over $\mathbf{w}$, the obtained near optimal weights can be concisely expressed by $\mathbf{w}_{opt} = \boldsymbol{\Sigma}_{H_0}^{-1}\mathbf{g}/\mathbf{1}^{\mathrm{T}}\Sigma_{H_0}^{-1}\mathbf{g}$ The i-th component of $\mathbf{w}_{opt}$, *i.e.*, $(\eta_i/\sigma_i^2)/\sum_{i=1}^N(\eta_i/\sigma_i^2)$, is the weight of sensor i. Consequently, the weighting ratio of the consensus protocol of (2) can be easily derived by $\delta_i = \eta_i/\sigma_i^2$. Applying $\mathbf{w}_{opt}$ to (8), we have

$$d^2(\mathbf{w}) = \frac{E_s^2}{2N} \sum_{i=1}^N \frac{h_i^4}{\sigma_i^4} \tag{9}$$

We can see that in terms of improving $d^2(\mathbf{w})$, the contributions from the sensors are independent, which is h_i^4/σ_i^4 for the ith sensor. And it is clear that a sensor under a high local SNR is able to increase $d^2(\mathbf{w})$ substantially while the contribution from a sensor experiencing low SNR can be negligible. Therefore, it is not reasonable to invest energy on a sensor of low SNR to pursue a slightly increase of $d^2(\mathbf{w})$.

According to (9), we define the *performance gain* for sensor i as

$$p_i = h_i^4/\sigma_i^4. \quad (10)$$

An effective distributed cooperative spectrum sensing scheme involves a set of sensors $\{v_{i_l}\}_{l=1}^{L}$ that can not only implement the distributed spectrum sensing algorithm, but also guarantee the condition of $\sum_{l=1}^{L} p_{n_l} \geq \Theta$, *i.e.*, where Θ is a predetermined threshold. From energy efficiency prospective, it is desirable to have a $\{v_{i_l}\}_{l=1}^{L}$ with minimum L.

Remark 1: The threshold Θ is determined by the target spectrum sensing performance. If we request a high sensing performance, we can set Θ to a large value, such that the sensor set can generate a large $d^2(\mathbf{w})$ and correspondingly, a high sensing performance. Moreover, the upper limit of Θ is determined by (9), which is $\overline{\Theta} = 2Nd^2(\mathbf{w}_{opt})/E_s^2$. This value corresponds to the situation where all the sensors are included for the cooperative spectrum sensing.

Remark 2: If we only consider the condition of Θ, the optimal sensor set can be found by selecting sensors one by one according to the descending order of their performance gains until Θ is surpassed. However, the applied distributed spectrum sensing algorithm requires the topology of the cooperative sensors being connected, which makes this optimization problem no longer straightforward.

III. Proposed Methods

For the energy efficiency optimization of distributed cooperative spectrum sensing, an essential component is a sensor selection mechanism to discover sensor sets that can successfully implement the distributed spectrum sensing algorithm while satisfying the desired performance. For this purpose, we design the following sequential sensor selection process, which is illustrated in Fig. 2. This process starts with an empty sensor set and adds one sensor a time until the threshold (Θ) is reached. At the first step, a sensor that is connected to the spectrum policy server will be selected to ensure the sensing results can be delivered to it. In the succeeding steps, feasible selections are restricted to the sensors that have connections to the previously selected ones. In order to improve energy efficiency, we want to find a sensor set containing as fewer entries as possible. We propose two evolutionary algorithms, *i.e.*, GA and PSO, are proposed to improve the energy efficiency.

Basically, with both GA and PSO, there is a population of random initialized candidate solutions that iteratively evolve towards a better fitness. For these two algorithms, it is pivotal to have an effective representation of each candidate solution as well as a proper fitness evaluation that is compatible with our optimization objective. Consequently, the following two methods are applied.

First, for the solution representation, we apply the priority based encoding method, which is proposed in [13]. With this method, each solution is represented by a set of priority values that are assigned to the sensors. Supposing a solution assigns the sensors in Fig. 2 with the priority values of $\{\psi_i\}_{i=1}^{5}$, this solution can be illustrated by Fig. 3. For the GA, this solution representation is known as a chromosome with each priority value being a gene. However, for the PSO, it is called a particle with the position specified by the priority values. Furthermore, in the sensor selection process, the feasible sensor with the highest priority value will be selected. Supposing we have $\psi_4 > \psi_3 > \psi_2 > \psi_5 > \psi_1$, the corresponding sensor selection order will be $v_2 \to v_4 \to v_3 \to v_1 \to v_5$. *Then*, for an valid fitness evaluation mechanism, it should yield a high fitness score for the solution that is able to discover an effective sensor set of small size. Considering this fact, we evaluate the fitness of a solution through the following two steps:1) apply the priority-encoded solution S_i to the sequential sensor process, and get the corresponding sensor set $\{v_j\}_{j=1}^{|S_i|}$; 2) calculate the fitness by $F_{S_i} = f(|S_i|)$. In these two steps, $|S_i|$ denotes the volume of the sensor set obtained by solution S_i; F_{S_i} is the fitness score of S_i; and $f(\cdot)$ is a monotonically decreasing function, such that a solution generating small valid sensor set will get a high fitness score. In this paper, we apply $f(x) = 1/x$ for both GA and PSO. Based on this solution representation and fitness evaluation method, the employed GA and PSO will improve the solution quality through different update rules. The flow charts of these two algorithms are shown in Fig. 4, which will be specifically described in the following two subsections.

A. Genetic algorithm based search

As shown by Fig. 4(a), the GA begins with initializing population. In the initialized population, a solution assigns each sensor with a distinct integer as the priority value. Although the GA also works if the priority values are set to continuous values, we still apply integers for the sake of conciseness. The solutions are evaluated by the fitness calculation process introduced before. Then, the termination condition will be checked to make judgment about whether to terminate the algorithm or not. In this paper, we set a maximum generation number as the termination condition. If the termination condition is not satisfied, elitist selection will be implemented based on the fitness score to keep the population size. The survived solutions go through crossover and mutation operators to generate offspring. The procedures of crossover and mutation can be illustrated in Fig. 5. With the crossover, a group of the survived solutions will be randomly selected based on the crossover rate, and paired as parents. A pair of parents generate the child through the position-based crossover operator that is illustrated in Fig. 5 (a). Generally, this operator first randomly copies some genes from one parent at the same positions for the child, and then complements the vacuum positions with genes from the other parent by a left-to-right scan. Then, with the probability of mutation rate, the newly generated children will mutate through the swap mutation operation, which is shown in Fig. 5(b). The new population expended by the offspring will go back to the fitness calculation step of the next generation.

B. PSO based search

The PSO also starts with population initialization. However, the priority values should be fractional since the update

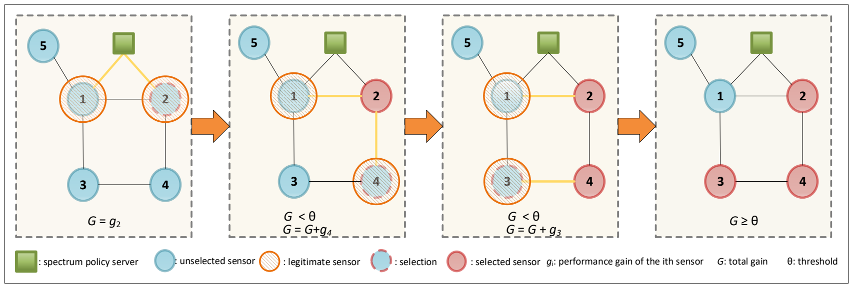


Fig. 2. Sequential sensor selection process for distributed cooperative sensing [9]. In this process, we pick one node a time until the summation of all the performance gains (G) of the selected nodes surpass a pre-set threshold (Θ). In each selection step, the legitimate candidate nodes for selection are those connected to one of the previously selected nodes.

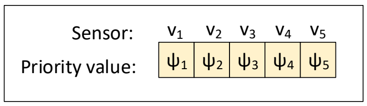
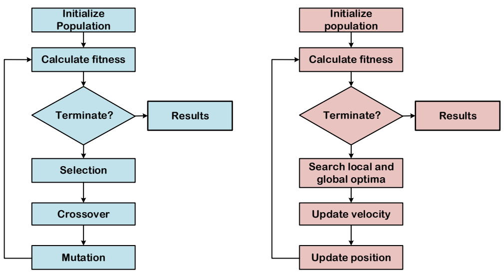


Fig. 3. An illustration of the priority-based encoding of a candidate solution.



(a) (b)

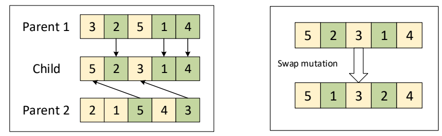
Fig. 4. (a) Flowchart of the GA, (b) Flowchart of the PSO.

rule PSO involves continuous functions. In this papre, we randomly smapled these initial value from the uniform distribution: $\mathrm{U}(0, 1)$. In the initialization stage, each candidate solution initializes its position with the priority value and its velocity with a zero vector of length N. For the ith candidate solution, we denote its position and velocity by $\Psi_{S_i}^n = [\psi_{i_1}^n, \psi_{i_2}^n, \ldots, \psi_{i_N}^n]^{\mathrm{T}}$ and $\Phi_{S_i}^n = [\phi_{i_1}^n, \phi_{i_2}^n, \ldots, \phi_{i_N}^n]^{\mathrm{T}}$, where n is the generation index of the PSO. The fitness score of a candidate solution will be calculated by the two-step fitness evaluation procedure introduced before. Then, based on the fitness score, the global best solution and the local best solution are searched for the update. Specifically, we denote the position of the global best solution, which achieves the highest fitness score at generation n, by $\Psi_{\mathbf{b}}^n$; and for solution S_i, its local best positon is $\Psi_{b_i}^n$, which leads it to the highest fitness score until generation n. With these two values, the velocity and position of S_i will be updated by

$$\Phi_{S_i}^{n+1} = \omega\Phi_{S_i}^n + \alpha r_1(\Psi_{\mathbf{b}}^{n-1} - \Psi_i^n) + \beta r_2(\Psi_{bi}^n - \Psi_{S_i}^n) \quad (11)$$

$$\Psi_{S_i}^{n+1} = \Psi_{S_i}^n + \Phi_{S_i}^{n+1} \quad (12)$$

where ω is the inertia weight; α and β are two positive constants; r_1 and r_2 are random numbers sampled from uniform distribution $U(0, 1)$. The fitness score of the updated candidate solutions will be calculated for the next generation. In this paper, we also set a maximum generation number as the termination condition for the PSO.



(a) (b)

Fig. 5. (a) The position-based crossover operator, (b) The swap mutation operator [13].

IV. Simulations and Analysis

In this section, we evaluate the proposed GA and PSO based methods with numerical simulations. The sensor networks we considered in this section contain 64 sensors. For simplity, we assume the transmitted primary signal is $s(k) = 1$, and the local noise level of the sensor are identical to each other which is $v_i(k) \sim \mathrm{N}(0, 1)$. The channel gains of the sensors are independent to each other and we sample these values from the Rayleigh distribution with the scale being 0.15 to simulate the low SNR environment. The signal sampling length M is set to 50. The distribtuted spectrum sensing algorithm proposed in [5] is applied and the performance gains of the sensors can be calculated based on (11). With energy detection, spectrum sensing ROC curves of these 64 sensors are shown with the black lines in Fig. 6. Clearly, the performance of each individual sensor is not good. However, if all the sensors cooperate together through the weighted consensus protocol of (3), the spectrum sensing performance can be boosted to the red line of Fig. 6. Moreover, denoting the total performance gain by $\overline{\Theta}$, a subset of sensors is able to achieve the performance specified by the blue lines if the summation of their performance gains is equal to $0.7\overline{\Theta}$. It should be noted that there are totally 10 blue lines which show the performance of 10 sets of sensors whose total performance gains are equal or approximately equal to $0.7\overline{\Theta}$. Each sensor set is obtained by randomly selecting one sensor a time until the total performance gain of the selected sensors surpasses $0.7\overline{\Theta}$. The spectrum sensing performance of different sensor sets may slightly differ from each other even if their total performance gains are the very close. However, this difference can be neglected in the low SNR environment. This is also the reason for the blue lines being close to each other. We can see that the spectrum sensing performance of the sensors with 70% of the total performance gain is already close to the red line. Thus, in our simulations, we set the threshold by

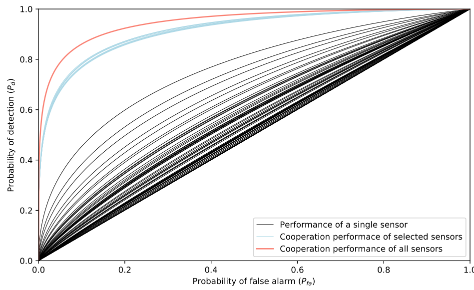


Fig. 6. Theoretical spectrum sensing performance. Each black line shows the detection performance of an individual sensor. The red line shows the performance under the cooperation of all 64 sensors. Each blue line shows the spectrum sensing performance under the cooperation of a subset of sensors in which the summation of their performance gain reachs the threshold (Θ).

$\Theta = 0.7\overline{\Theta}$. Note that Θ can be set to other values based on the specific requirement.

In our simulation, we assume that the sensors are deployed to a regular grid structure with certain variations. The variations are introduced to simulate the real-world environment since the sensor's installation position may be affected by other constraints in reality. Our proposed GA and PSO based methods are applied to the sensor network to optimize the energy efficiency of the sensor network through the sequential sensor selection process. For the GA, the population size is set to 32; the crossover rate and the mutation rate are set to 0.5 and 0.1, respectively; and the total *generation number is 1000*. For the PSO, we have $\omega = 0.5$, $\alpha = 0.9$, $\beta = 0.8$; the population size is also 32; and the *generation number is set to 200*. We evaluate our proposed method on 100 of such randomly generated sensor networks rather than on only one sensor network to avoid bias. Moreover, to better evaluate our methods, we also apply a greedy algorithm as the baseline. With the greedy algorithm, the feasible sensor with the largest performance gain will be selected at each step in the sequential sensor selection process. The results of all these three methods are shown in Fig.7. It can be observed that, when selecting the

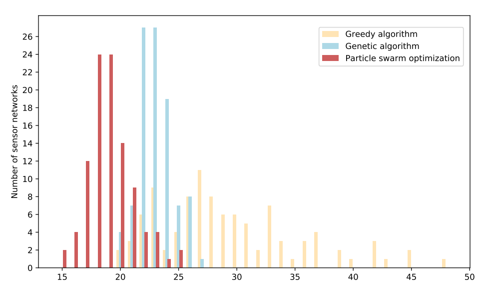


Fig. 7. The size distribution of the sensor sets obtained by the three comparative approaches over the 100 sensor networks.

sensors with greedy algorithm for the sensor networks, the size of the obtained sensor sets has a relative large variation. However, the variation is much smaller when using the GA and PSO. With greedy algorithm, the average number of the selected sensors over the 100 sensor networks is 29.41. With the GA and PSO, this value will reduce to 23.08 and 19.09, respectively. This result demonstrates that comparing with the greedy algorithm, the proposed GA and PSO methods are more likely to find a smaller sensor set to achieve the same spectrum sensing performance. We can save about 22% or 35% more energy on average if we apply the corresponding proposed methods to pick the cooperative sensors instead of using the greedy algorithm. Statistically, PSO performs best among these three methods.

V. Conclusion

In this paper, we study the energy efficiency optimization for distributed cooperative spectrum sensing. The objective is to achieve the predefined spectrum sensing performance with as few sensors as possible. Two evolutionary search methods, *i.e.*, GA and PSO, are proposed. These two algorithms improve the solution quality through different mechanism. Simulation results demonstrate that both of these two methods can achieve better performance than the baseline algorithm, *i.e.*, greedy algorithm. Moreover, comparing with GA, the PSO is able to obtain solutions of higher quality even with a smaller generation number.

VI. Acknowledgement

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References

[1] J. Mitola, "Cognitive radio—an integrated agent architecture for software defined radio," 2000.
[2] S. Haykin, D. J. Thomson, and J. H. Reed, "Spectrum sensing for cognitive radio," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 849–877, 2009.
[3] G. Ganesan and Y. Li, "Cooperative spectrum sensing in cognitive radio networks," in *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005.* IEEE, 2005, pp. 137–143.
[4] Z. Li, F. R. Yu, and M. Huang, "A distributed consensus-based cooperative spectrum-sensing scheme in cognitive radios," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 1, pp. 383–393, 2010.
[5] W. Zhang, Y. Guo, H. Liu, Y. J. Chen, Z. Wang, and J. Mitola III, "Distributed consensus-based weight design for cooperative spectrum sensing," *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 1, pp. 54–64, 2015.
[6] S. Maleki, A. Pandharipande, and G. Leus, "Energy-efficient distributed spectrum sensing for cognitive sensor networks," *IEEE sensors journal*, vol. 11, no. 3, pp. 565–573, 2011.
[7] R. Deng, J. Chen, C. Yuen, P. Cheng, and Y. Sun, "Energy-efficient cooperative spectrum sensing by optimal scheduling in sensor-aided cognitive radio networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 2, pp. 716–725, 2012.
[8] P. Cheng, R. Deng, and J. Chen, "Energy-efficient cooperative spectrum sensing in sensor-aided cognitive radio networks," *IEEE Wireless Communications*, vol. 19, no. 6, pp. 100–105, 2012.
[9] H. He and H. Jiang, "Deep learning based energy efficiency optimization for distributed cooperative spectrum sensing," *IEEE Wireless Communications*, 2019.
[10] L. Davis, "Handbook of genetic algorithms," 1991.
[11] J. Kennedy, "Particle swarm optimization," *Encyclopedia of machine learning*, pp. 760–766, 2010.
[12] Z. Quan, S. Cui, and A. H. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *IEEE Journal of selected topics in signal processing*, vol. 2, no. 1, pp. 28–40, 2008.
[13] M. Gen, R. Cheng, and D. Wang, "Genetic algorithms for solving shortest path problems," in *Proceedings of 1997 IEEE International Conference on Evolutionary Computation (ICEC'97).* IEEE, 1997, pp. 401–406.