Optimization of Cognitive Radio Secondary Base Station Positioning and Operating Channel Selection for IoT Sensor Networks

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***Abstract*—In our paper, a novel method is proposed to obtain the optimal positions of secondary base stations (SBSs) for cognitive radio Internet of Things (IoT) sensor networks and to select the optimal operating channel in order to maximize the secondary capacity, while also protecting the primary systems. We proposed an appearance probability matrix for secondary IoT sensor devices in order to maximize the supportable number of sensor devices based on the optimal deployment case and probability. We derived fitness functions based on the above objectives and also considered the constraint. The particle swarm optimization (PSO) technique is used to find the best position and operating channel of SBSs.**

Keywords—IoT sensor networks, secondary base station, optimal positioning, operating channel selection, secondary appearance probability.

I. INTRODUCTION

Due to the increasing demand for spectrum resources, cognitive radio (CR) networks have received a lot of research attention in attempts to efficiently utilize limited spectrum resources[1]. In a CR wireless network, primary users (PUs) can share the spectrum with secondary IoT sensor devices (SSDs), the success of the network lies in enhancing spectrum and resource allocation. Great research efforts have been made to further develop the efficiency of spectrum utilization. However, it should be noted that placing the base station at an inappropriate location and selecting an incorrect channel will increase the interference and minimize the QoS directly. The researchers built a cost function for the optimization process that can give the optimal position of a base station[2], this allowed the researchers to calculate the minimal emitted power for that optimal position. [3] also gives the optimal base station locations based on the interference power. Additionally, focusing on interference management among SSDs and PUs can also play a key role in resource allocation. In [4], researchers presented a general resource-allocation framework that optimizes the power and channel allocation for SSDs, in order to solve the problem of unfair resource aggregation caused by disadvantageous positioning.

In our paper, the work aims to maximize the secondary capacity while also guaranteeing an interference threshold for primary subjects and maximizing the supportable number of secondary users, which is IoT sensor devices in our case, based on the optimal location, operating channel selection, and IoT sensor devices appearance probability. The rest of this paper is organized as follows. In Section II, system model and problem formulation are presented. In Section III, the particle swarm optimization (PSO) algorithm used to determine the optimal SBS locations and channel selection for cognitive IoT sensor network is explained. In Section IV, the performance of the proposed method is evaluated. Section V provides our conclusions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System model

As shown in Fig. 1, primary base station (PBS) will receive interference from cognitive IoT sensor devices (i.e. SSDs), base station of IoT sensor network (i.e. SBSs), and other primary systems (including PBSs and PUs that use the same channel as the PBS). In Fig. 1, the blue line denotes the interference suffered by the PBS. PUs will receive interference from SUs, SBSs, and other primary systems that use the same channel. The black line in Fig. 1 shows the interference received by a PU. Concerning the secondary systems, SSDs will receive interference from PBSs and PUs, as well as other secondary systems. Similarly, SBSs will receive interference from other SBSs, SSDs, PBSs, and PUs that share the same channel. The red and orange lines indicate the interference experienced by the SSDs and SBS, respectively.

However, in our model, we ignore the interference from primary systems and assume that they are well controlled by the primary operator. We only consider the uplink channel of primary systems, and assume that secondary systems will use primary's uplink channels. The secondary system also knows the PBS positions and operating channel before determining the SBS positions and matched channel.

B. Problem formulation

In our model, we proposed a novel concept: the IoT sensors appearance probability. As shown in Fig. 2, we divide the whole space into small equally-sized boxes, and every unit area ranges from 0 to 1; this stands for the probability of the appearance of an IoT sensor device. We assume that no more

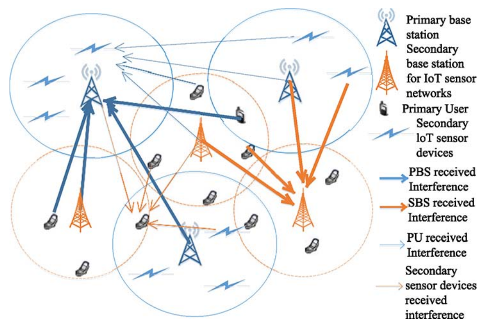

Fig. 1. System Model.

than one SSD can exist in each unit area. There are three possible cases in every unit site: (a) one base station (SBS or PBS) and one SSD, (b) one SSD, or (c) one SBS or one PBS. We know the SSD appearance probability before deploying the SBS, and the probabilities in every unit area are independent of each other.

We consider the $Friis$ free-space path loss model, which is based on the inverse square law of distance. We calculate the average SINR at the ith unit area on the jth channel belonging to the kth SBS:

$$S\_ESINR_{k,i}^{j} = \frac{P_{sb}|h_{k,i}^{j}|^2}{\underbrace{\sum_{\forall l\in\{PB^j\}} P_{pu}\left|h_l^j, h_i^j\right|^2}_{A} + \underbrace{\sum_{\forall m\in\{SB^j\},m\neq k}\frac{1}{N_u}\left[P_{ssd}\sum_{\forall q\in\{SB_{m,q}\}}\left|h_{q,i}^j\right|^2 P_q + P_{sb}\left|h_{m,i}^j\right|^2\right]}_{B} + n_0} \quad (1)$$

Here, part A is the average interference from PUs, and part B stands for the average interference from other secondary systems that use the jth channel. N_u is the number of unit areas covered by a SBS. P_{sb} and P_{su} are transmission power of SBSs and SSDs, respectively. q means the $q-th$ unit cell, and $SB_{m,q}$ is the set of unit cells q that belong to the mth SBS. n_0 is the thermal noise power. It should be noted that, because we do not know the positions of PUs, we assume that PUs are uniformly distributed within the PBS range. Therefore, we approximate the average as $\mathrm{E}[h_{w,i}^j] \approx h_{l,i}^j$, where w is the $w-th$ PU. l is the $l-th$ PBS. Additionally, $|\mathrm{h}_{k,i}^j|^2$ is the channel gain between the kth SBS and the ith unit area.

For PBSs, we consider the worst case for primary systems. In worst case, all of the PUs are distributed on the edge of the PBS service range that is closest to the SSD and will give intense interference to the SSD. The worst SINR at the lth PBS on the jth channel can be presented as shown in (2).

Similarly, part X represents the interference from primary users; however, we ignore this part in our model. Y indicates the

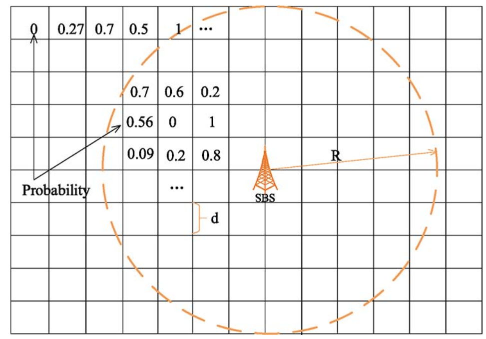

Fig. 2. Small unit boxes of secondary systems.

$$P\_WSINR_l^j = \frac{P_{pu}|h_w^j|^2}{\underbrace{\sum_{\forall l\in\{PB^j\}} P_{pu}\left|h_{l1}^j, h_l^j\right|^2}_{X} + \underbrace{\sum_{\forall m\in\{SB^j\},m\neq k}\frac{1}{N_u}\left[P_{ssd}\sum_{\forall q\in\{SB_{m,q}\}}\left|h_{q,l}^j\right|^2 P_q + P_{sb}\left|h_{m,l}^j\right|^2\right]}_{Y} + n_0} \quad (2)$$

$|\mathrm{h}_w^j|^2 = \frac{1}{{R_p}^2}$, ${R_p}^2$ is the PBS coverage radius. The capacity can power. h_w^j is the worst channel gain from PU and PBS, here interference from secondary systems. P_{pu} is PUs transmitter be calculated based on the Shannon equation:

For the PBS: $$C_l = Blog_2\left(1 + P\_WSINR_l^j\right) \quad (3)$$

For the SSD: $$C_i = Blog_2\left(1 + S\_ESINR_{k,i}^j\right) \quad (4)$$

where, B is the bandwidth. We also present SINR constraints. That means, the SINR of a SSD should greater than the SINR of the SSD threshold. Similarly, the SINR of every PBS should satisfy the primary SINR threshold. Meanwhile, maximize the supportable number of SSDs:

$$F_{\max\_SSDs} = \sum_{m=1}^{N_s}\sum_{\forall q\in ssd_m} P_q \quad (5)$$

III. Proposed Method for Determining the Optimal Location and Operating Channel Selection of a SBS Using PSO

In this work, the particle swarm optimization algorithm (PSO) is invoked to obtain an optimized solution. In PSO, the potential solutions are called particles, and these candidate solutions are referred to as swarms of particles. Each of these is characterized by its position and velocity based on its own best value ($pbest$), as well as the best value in the whole search space ($gbest$). Then, every particle adjusts its value (position) toward to its $pbest$ and $gbest$ at each iteration. This movement is governed by the equations:

$$V(t+1) = wV(t) + C_1r_1\left(pbest - X(t)\right) + C_2r_2\left(gbest - X(t)\right) \quad (6)$$

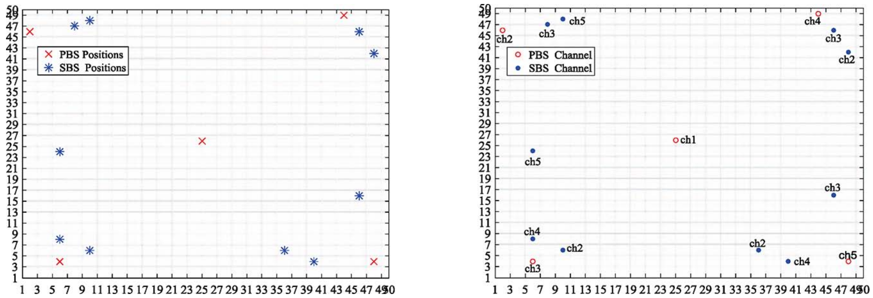

Fig. 3. Optimal topology for SBS is for IoT sensor networks positions and operating channel.

$$X(t+1) = X(t) + V(t+1) \quad (7)$$

Here, w is the weight inertia, C_1 *and* C_2 are the confidences in other coefficients, and r_1 *and* r_2 are two independently-generated random numbers from [0,1]. $X(t)$ and $V(t)$ are the position and velocity of t second particles, respectively. The objective functions described in the previous section are then used in the fitness function and optimized by the PSO algorithm.

In our model, we have two particles: SBS location and operating channel. The practical implementation of classical PSO mainly involves the following steps. 1) Parameter initialization. 2) Evaluate the desired objective function of each particle. 3) Compare each particle's current fitness value with the previous $pbest$. 4) Determine $gbest$ of the swarm from the total $pbest$ value. 5) Update the velocity and positions of every particle using (5) and (6). 6) Update the generation number using t=t+1. Check the current iteration number; if this is less than the total iteration, go back to step 3, otherwise, go to step 7. 7) Output the optimal solution, including $gbest$ and the current fitness value.

IV. Simulation Results

In the simulation, we divide the total area into 50×50 unit areas. Every number stands for a position and will be mapped to the corresponding coordinates. We set the number of channels to five, and the selection space is $C = \{1, 2, 3, 4, 5\}$. The topology is created by 10 secondary systems and 5 primary systems that share 5 channels. Fig. 3 shows the best topology for the optimal SBS locations and operating channel, respectively. As can be seen from the picture, we divided every unit area into $2 * 2$. That means, each small box has 4 unit area. We assumed that each base station was located in the center of the unit site, and we obtained the base station's coordinates by combining its x and y axis locations. Fig. 4 shows the multi-objective result that were determined by PSO during 1000 iterations. allocation in cognitive radio networks. The proposed algorithm can maximize the secondary system's capacity while also enhancing the primary system's performance. Our algorithm also can maximize the number of supportable IoT sensor devices based on the optimal positions of SBSs. In addition, the distributed scheme has lower complexity and fundamentally improves the total system's performance and capacity.

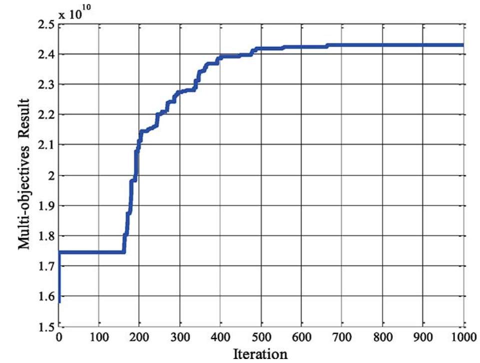

Fig. 4. Multi-objective result obtained from PSO.

V. Conclusion

In this paper, we proposed a distributed scheme that determines the optimal location and operating channel of SBSs of IoT sensor networks to manage the interference and resource allocation. The proposed algorithm maximized the secondary system's capacity along with primary system's performance and number of supportable IoT sensor devices. In addition, the distributed scheme has lower complexity and fundamentally improves the total system's performance and capacity. The simulation results verify benefits our proposed protocol.

Acknowledgment

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