

# Energy-Efficient Resource Allocation and Spectrum Sensing for Heterogeneous Cognitive Radio Network based on Two-Tier Crossover Genetic Algorithm

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**Abstract**—Cognitive Radio (CR) is considered an attractive technology to deal with the spectrum scarcity problem. Multi radio access technology (multi-RAT) can improve network capacity. Thus, multi-RAT embedded in a cognitive Radio Network (CRN) is a promising paradigm for developing spectrum efficiency and network capacity in future wireless networks. In this study, we consider a new CRN model in which the primary user networks consist of heterogeneous Primary Users (PUs). Specifically, we focus on the Energy-Efficient Resource Allocation (EERA) problem for CR. We propose a two-tier cross over genetic algorithm-based search scheme to obtain an optimal solution in terms of the power and bandwidth. Spectrum sensing is the basic and essential mechanisms of Cognitive Radio (CR) to find the unused spectrum. Energy detection based spectrum sensing has been proposed. The simulation results show the proposed algorithm is stable and has faster convergence. Our proposal can significantly increase the energy efficiency.

**Keywords**—Cognitive Radio Network; Energy-Efficient Resource Allocation; Multi-RAT; Radio Environment Map; Two-tier Crossover Genetic Algorithm.

**Abbreviations**—Cognitive Radio (CR); Cognitive Radio Network (CRN); Energy-Efficient Resource Allocation (EERA); Primary Users (PUs).

## I. INTRODUCTION

WITH the development of wireless communication technology, spectrum resources have become increasingly scarce. In the past 10 years, researchers have mostly focused on new techniques and innovations to achieve a higher spectral efficiency, such as cognitive radio (CR). CR users, which are referred to as secondary users (SUs), share wireless channels with licensed primary users (PUs) who have already been assigned a specified spectrum, as long as the interference to the PU is kept below present thresholds (called interference

temperatures). In addition, rapidly rising energy costs and increasingly rigid environmental standards have led to an emerging trend of addressing the energy efficiency of wireless communication technologies [Miao et al., 4].

CR plays an important role in improving the energy efficiency of wireless networks because, from the green communication perspective, the spectrum is a natural resource that should be shared rather than wasted. Recently, because of its potential for performance improvement, multi-radio access technology (multi-RAT) has recaptured the attention of researchers. It has been shown that performance can be improved by more effective resource utilization

among multi-radio access network. Therefore, multi-radio access (MRA) system, where data streams are split into multiple sub streams which transfer simultaneously, becomes the focus of researches. Many issues, such as how to reduce energy consumption, have yet to be resolved the problem. By a low-power and low-cost short-range device-cellular telecommunications base stations, femto cell technology provide improved cellular coverage within a building by providing a high-quality short-distance link to the user equipment. Consequently, it is a promising solution to reduce energy consumption for wireless networks.

By harnessing the advantages of femto cell and CR technology, a cognitive femto cell is a promising potential component for future heterogeneous networks. However, compared with non-CR femto cells, a cognitive femto cell requires more transmission power to support extra signal processing, such as spectrum sensing. Thus, it cannot ignore energy efficiency in this network. An energy-efficient resource allocation (EERA) for a cognitive femto cell has been addressed in Xie *et al.* proposed a three-stage Stack el berg game based scheme. In authors proposed an approach for selecting an optimal base station in two-tier networks to reduce the cross-tier interference. An *et al.* introduced a low complexity iteration algorithm based on a gradient-assisted binary search algorithm for an optimization problem. Chen *et al.* proposed a new energy-efficient power allocation scheme to balance the trade-off of spectral efficiency and energy efficiency. Motivated by the aforementioned researches, embedding multi-RAT and femto cell technology in the cognitive radio network (CRN) is a promising paradigm, which not only to improve network capability, but energy efficiency. For this reason, a new CRN model, which includes multi-RAT based PU networks (Pest) and cognitive femto cell based SU networks (SNets), is developed in this study. In particular, we focus on EERA of SNets in the overlapping region of heterogeneous PNETs coverage. At this point, it is different from previous works only assume homogeneous PNETs. Wang *et al.* assumed multiple PU types in the system model and studied the joint sub carrier and power allocation problem for orthogonal frequency division multiple access (OFDMA)- based CR networks from an energy efficiency (EE) perspective. The barrier method was developed to work out the (near) optimal solution assuming that the system has perfect knowledge of the channel state information (CSI). However, it is difficult to guarantee CSI is perfect in realistic wireless communication system. That is, it is hard to obtain an upper bound on the achievable EE with channel estimation errors. Inspired by, we define the EERA of heterogeneous CRN as a multidimensional nonlinear constrained optimization problem demonstrated as below. It aims that maximize energy efficiency of the whole system. The genetic algorithm (GA), which is a search heuristic that mimics the process of natural evolution, is an ideal search method to solve this complex optimization problem; compared with many other search methods, it has significant global search capacity and robust problem-solving. However, conventional GA has numerous drawbacks, such as slow

convergence speed, limited search space, and low stability. Hence, conventional GA is not suitable for our study. So, we propose a two-tier crossover GA to improve conventional GAs' performance. Some distinct features of this study are as follows [Ismail *et al.*, 5].

Concentrating on the case where SNets are located within heterogeneous PNETs overlapping region and SNets have equal opportunity to share the different spectrum resources. To the best of our knowledge, it is the first time to focus on such a case explicitly. - Introducing the radio environment map (REM) to maintain synchronization between the PNETs and SNets. Proposing a two-tier crossover GA method to search optimal solution. The simulation results show that the proposed method has better convergence. The rest of this paper is organized as follows: we introduce the system model. Then, the formulation of EERA. We propose a two-tier crossover GA-based method to search for an optimal solution.

## II. EXISTING WORK

This paper is used under for improve energy efficient and improve spectrum accuracy for cognitive radio network [Li *et al.*, 1]. With explosive growth of high-data-rate applications, more and more energy is consumed in wireless networks to guarantee quality of service. Therefore, energy-efficient communications have been paid increasing attention the background of limited energy resource and environmental-friendly transmission behaviours. In this article, basic concepts of energy-efficient communications are first introduced and then existing fundamental works and advanced techniques for energy efficiency are summarized, including information-theoretic analysis, OFDMA networks, MIMO techniques, relay transmission, and resource allocation for signalling. Some valuable topics in energy-efficient design are also identified for future research [Guler & Yener, 2]. This paper presents a novel cross-tier interference management solution for coexisting two-tier networks by exploiting cognition and coordination between tiers via the use of agile radios. The cognitive users sense their environment to determine the receivers they are interfering with, and adapt to it by designing their pre coders using interference alignment (IA) in order to avoid causing performance degradation to nearby receivers. The proposed approach judiciously chooses the set of users to be aligned at each receiver as a subset of the cross tier interferers, hence is termed selective IA. The proposed solution includes identification of the subspace in which cross-tier interference signals would be aligned followed by a distributed algorithm to identify the pre coders needed at the selected interferers. The intra-tier interference is then dealt with using minimum mean squared error (MMSE) interference suppression. Numerical results demonstrate the effectiveness of selective IA for both uplink and downlink interference management [Wang *et al.*, 3]. This paper we study the Resource Allocation (RA) in Orthogonal Frequency Division Multiplexing (OFDM)-based Cognitive Radio (CR) networks, under the

consideration of many practical limitations such as imperfect spectrum sensing, limited transmission power, different traffic demands of secondary users, etc. The general RA optimization framework leads to a complex mixed integer programming task which is computationally intractable. We propose to address this hard task in two steps. For the first step, we perform sub channel allocation to satisfy heterogeneous users' rate requirements roughly and remove the intractable integer constraints of the optimization problem. For the second step, we perform power distribution among the OFDM sub channels. By exploiting the problem structure to speed up the Newton step, we propose a barrier-based method which is able to achieve the optimal power distribution with an almost linear complexity, significantly better than the complexity of standard techniques. Moreover, we propose a method which is able to approximate the optimal solution with a constant complexity. Numerical results validate that our proposal exploits the overall capacity of CR systems well subjected to different traffic demands of users and interference constraints with given power budget [Gür et al., 6].

**2.1. System Model**

We consider an infrastructure-based heterogeneous cognitive radio network (HetCRNet) with multiple heterogeneous PNETs and multiple SNETs, where centralized cognitive base stations coordinate the resource allocation. Each SNETs is present either in a region of a PNET (i.e., Areas 1 and 2) or in overlapping regions such as Areas 3 and 4 where more than two heterogeneous PNETs coexist. The PNETs may be LTE, Wi\_MAX, Wi-Fi, or other wireless network with different coverage and operate on different spectrum frequency. In an overlapping region, there exist a cognitive base station (Cognitive BS), multiple macro cell secondary users (MSUs), multiple femto cells, and multiple femto cell secondary users (FSUs) [Xie et al., 7].

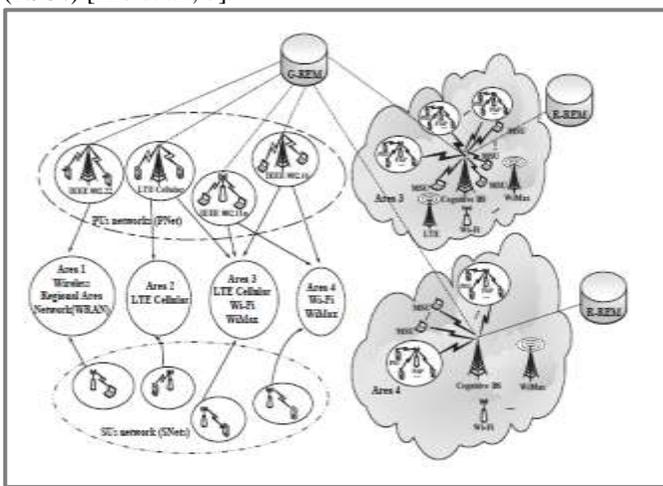


Figure 1: Heterogeneous Cognitive radio network (HetCRNet)

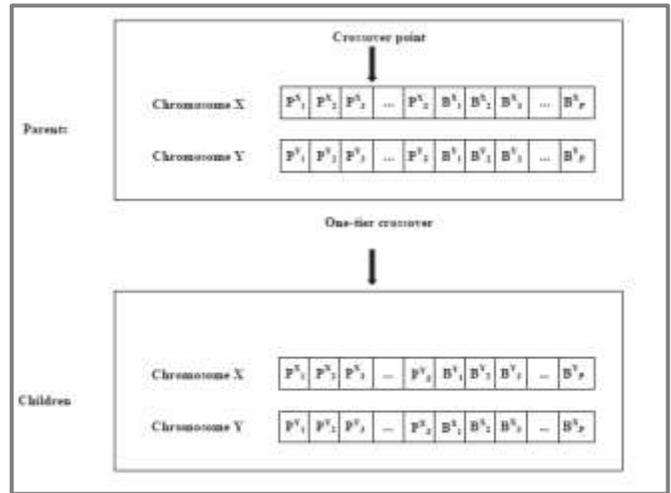


Figure 2: One-tier Crossover

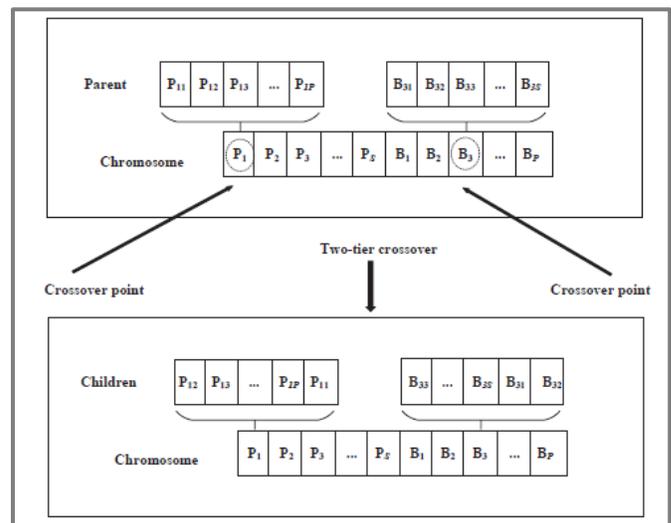


Figure 3: Two-tier Crossover

**2.2. Problem Formulation**

**2.2.1. Energy-Efficient Resource Allocation for Femtocell**

We adopt the COST-Hata propagation loss model as a signal propagation model in here. In practical systems, there are two typical types of sensing errors: *Miss Detection* (MD), which occurs when the CR system fails to detect the PU's signals; the other is *false alarm* (FA), which means the CR network identifies the band of sub-channel is unavailable but it is Vacant actually. We denote the MD probability and FA probability [Estrada et al., 8].

$$\eta = \frac{\omega \log_2(1 + \frac{h^2 p}{\sigma^2})}{pa + p}$$

The energy efficiency (EE) in bits per joule of the femto cell is given by

$$\eta = \frac{\sum_{k=1}^k R_k}{\sum_{k=1}^k POW_k + POW_c}$$

### 2.2.2. Energy-Efficient Resource Allocation for MSU

The optimal problem analyzed in a multidimensional nonlinear constrained optimization problem with high complexity. To simplify the theoretical analysis, we convert the maximization problem into a minimization problem as follows:

$$\min_{\rho k, nRk, n} \eta EE(\rho k, nRk, n) = \frac{\sum_{k=1}^k \sum_{n=1}^n \rho k, n POWk, n + POWc}{\sum_{k=1}^k \left( \sum_{n=1}^n \rho k, n \log(1 + POWk, n Xk, n) \right)}$$

$$\max_{\rho k, n POWkn} = \frac{\sum_{k=1}^k \left( \sum_{n=1}^n \rho k, n \log(1 + POWk, n Xk, n) \right)}{\sum_{k=1}^k \sum_{n=1}^n \rho k, n POWk, n + POWc}$$

According to this equation, we can meet the objectives of the optimal problem by minimizing the power consumption and maximizing the data transmission rate [An et al., 9].

### 2.2.3. Spectrum Allocation Algorithm for Femtocell or MSU

The signal-to-interference-plus-noise ratio (SINR) of MSU *m* served by Cognitive BS *a* through the *i*<sup>th</sup> sub-channel can be represented as

$$SINR_{m,a}^i = \frac{\alpha_a |h_a^i|^2 POW_a}{\sum_{b \neq a} \sqrt{a_b} |h_a^i|^2 POW_b + N_a^2}$$

$$SINR_{f,a}^i = \frac{|h_a^i|^2 \overline{SINR}_a}{\sum_{b \neq a} \sqrt{a_b} |h_a^i|^2 \overline{SINR}_a + 1}$$

## III. PROPOSED METHOD

Energy detection based spectrum sensing has been proposed which is used for Improving spectrum efficiency rather than reducing false alarm Probability and also Improve energy efficiency. To introduce a radio environment map to manage the resource allocation and network synchronization. The simulation results show the proposed algorithm is stable and has faster convergence and FAP, MDP. Our proposal can significantly increase the energy efficiency [Chen et al., 10].

### 3.1. Chromosome and Fitness Function

A Chromosome and sub-chromosome structures are shown as Figs. 2 and 3, respectively. One chromosome represents a feasible solution, which consists of (P + S) sub chromosomes. The object of EERA is transmitting more data with low transmission power. Hence, we propose an aggregate weighted fitness function as shown below.

$$Fitness = \sigma_1 f_{\min}^{power} + \sigma_2 f_{\max}^{rate}$$

$$f_{\min}^{power} = 1 - \frac{P_s}{N.P_{\max}} \quad f_{\max}^{rate} = 1 - \frac{r_s}{N.r_{\max}}$$

### 3.2. Evolutionary Operators

In conventional GAs, the evolutionary operators (i.e., crossover and mutation) work with a constant probability. However, it is not suitable for multiple object fitness function. Thus, we adopt the adaptive adjustment method in to adjust the crossover and mutation probabilities according to fitness function. The probability can be obtained as follows:

$$\begin{cases} \mu 1 = \mu 2 = 0.01 \frac{f_{\max} = f_{avg}}{f_{\max} = f_{\min}}, & \text{if } f_{\max} \succ f_{avg} \\ \mu 1 = \mu 2 = 0.01, & \text{if } f_{\max} = f_{avg} \end{cases}$$

### 3.3. Computational Complexity Analysis

According to the analysis in the previous section, the computational complexity of the proposed scheme includes the encoding, calculating fitness, and two-tier crossover steps. In this study, we adopt an encoding method referred of binary encoding. The order of the genes is immaterial in this encoding method, so it has less computational complexity and computational time. In the two-tier crossover, the proposed GA can obtain ((K + M) + P) chromosomes. Thus, we can set a large population size in the initialization.

## IV. SIMULATION ENVIRONMENT

### 4.1. Algorithm

The pseudo code for TTCS

### 4.2. Input

- M: Size of population
- $\gamma$  : Rate of mutation
- N: Number of iterations
- $\delta$ : Rate of crossover

### 4.3. Output

- Y: Solutions
- Begin
- // Initial
- 1. Sense the environment for inputs.  $\eta$
- 2. Convert the inputs into chromosomes by encoding them.
- 3. Generate M feasible random solutions.
- 4. Save them in population Pop.
- //Loop until termination criteria is reached.
- For each  $i \in [1, N]$  do
- // Selection based on fitness function
- 6. Select the best individuals in Pop.
- 7. Save them in Pop1.
- End for
- //Loop2 start: Crossover and mutation
- 8. Select two parents from Pop1.
- 9. Perform two-tier crossover operation.

10. Accumulate the crossover progress value.
  11. Perform mutation operation.
  13. Update the offspring value in Pop2.
  14. Accumulate the mutation progress value.
- ```
//Loop2 end
// Progress value adjustments
15. Calculate crossover progress value, adjust crossover rate.
16. Calculate mutation progress value, adjust mutation rate.
// Update Pop
17. Pop1 = Pop1 + Pop2
//End loop1
// Best solution
18. Return the best solution Y in Pop.
```

### V. SIMULATION RESULTS

The above Figure the convergence of the TTCS method with different population scales. The objective function curve gradually converges, but the speed is slow. The speed is more than 900 iterations, even for only 2 PNETs and 10 SUs. However, the size of the population obviously affects the convergence speed; the larger population size is, the faster speed converges. Because there is a large number of good genes for searching optimal solution in large population. Fig. 4 shows that the relationship between energy efficiency and the number of SUs in one PNET. From this figure, we can observe energy efficiency improve by SUs increase. That is, the more SUs are, and the higher energy efficiency is. It is due to the more chances are offered to cooperate when SUs increase in one PNET.

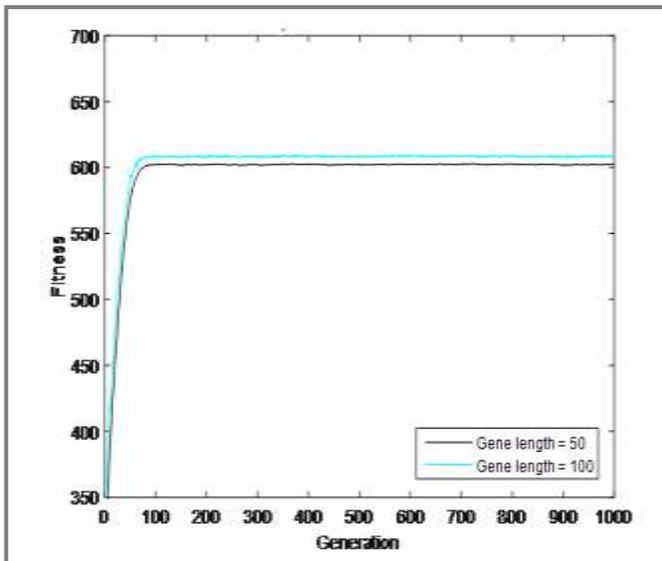


Figure 4: Convergence of the TTCS Method

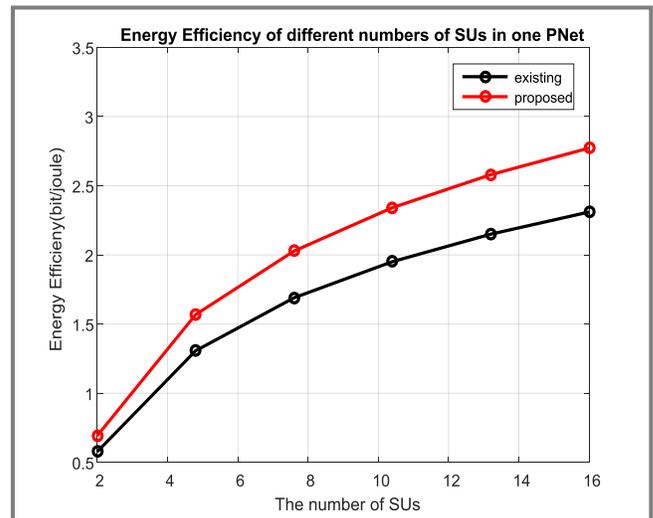


Figure 5: Energy Efficiency of Different Numbers of SUs in One PNET

Figure 5 shows that the relationship between energy efficiency and the number of SUs in one PNET. From this figure, we can observe energy efficiency improve by SUs increase. That is, the more SUs are, and the higher energy efficiency is. It is due to the more chances are offered to cooperate when SUs increase in one PNET.

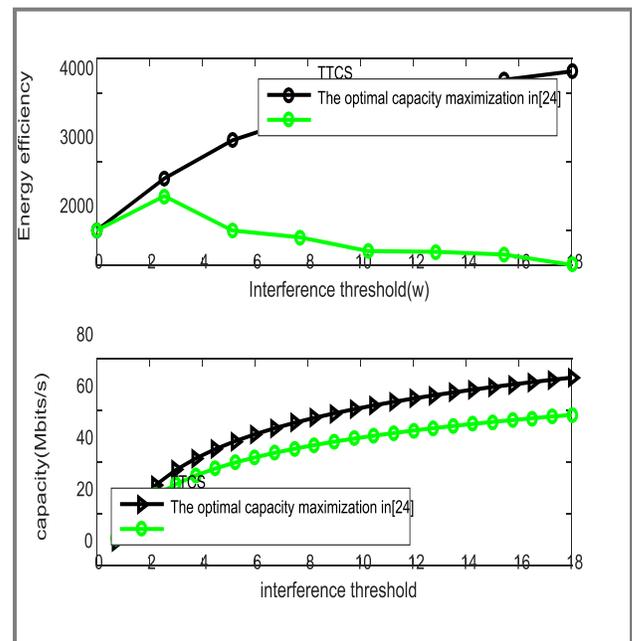


Figure 6: Computation Time of TTCS compare with Method Proposed

Figure 6 shows the compare between the TTCS and proposed scheme in [Wang et al., 11] from energy efficiency and capacity efficiency, respectively. We assumed MSU transmission power is 0.5 mW. Both figures show that as the interference threshold increases, the energy efficiency and capacity of the MSU increase. Although the capacity of [Wang et al., 11] is higher than TTCS by 27%, its energy efficiency is lower than TTCS about more than 64% when  $I_{Th} = 2.1 \times 10^{-6} W$ . This result shows that TTCS could achieve a good trade-off between capacity and energy.

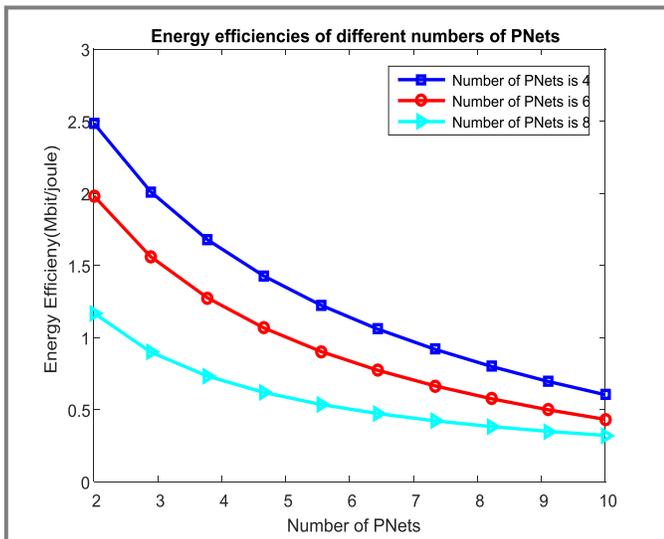


Figure 7: Energy Efficiencies of different Numbers of PNETs

Figure 7 shows the system performance (i.e., energy efficiency) with different cases in which there are different numbers of PNETs. The energy efficiency of system decreases as the PNETs increase since more extra energy consumed owing to distinguish are interference exist between the user and base different PNETs. More SUs leads to greater energy efficiency as illustrated in Figure 5. We assume only standalone femto cell in our system model. There is no co-tier interference among standalone femto cells. Thus, there station (either Cognitive BS or FAP): Outdoor-only and indoor only. Without loss of generality, we consider outdoor-only in this paper.

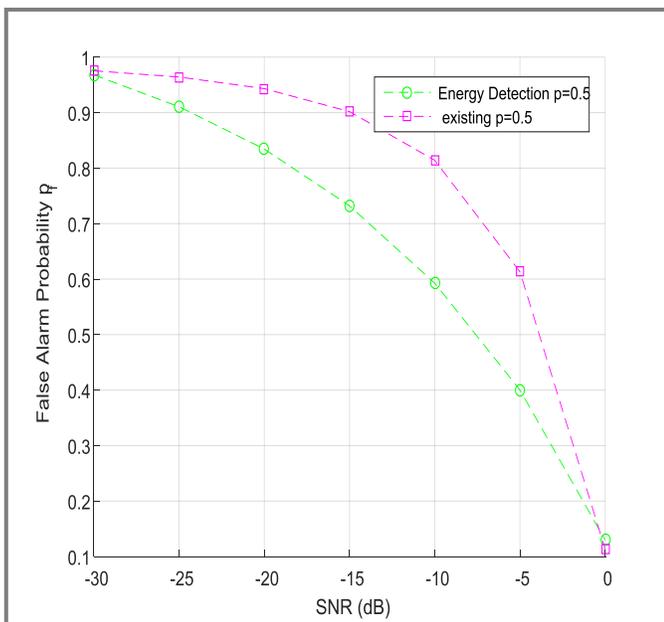


Figure 8: False Alarm Probability ( $p_f$ ) versus SNR (dB)

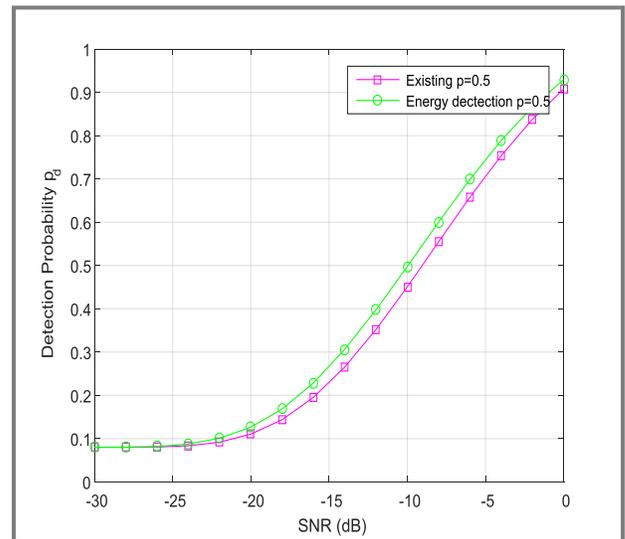


Figure 9: Detection Probability  $p_d$  and SNR (dB)

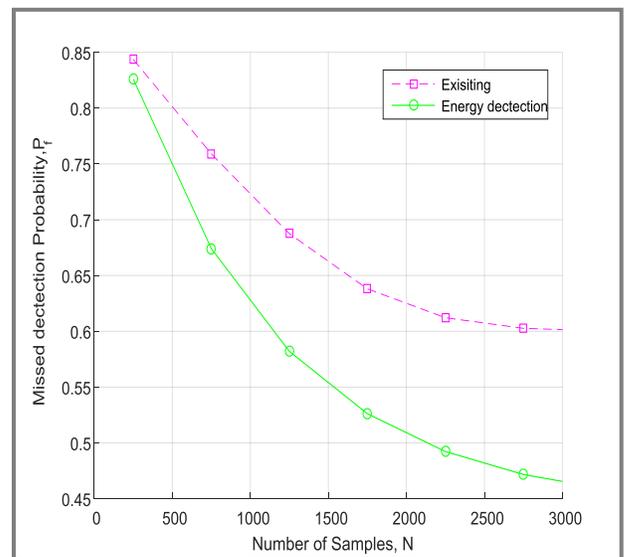


Figure 10: Missed Detection Probability  $P_f$  with number of Samples (N)

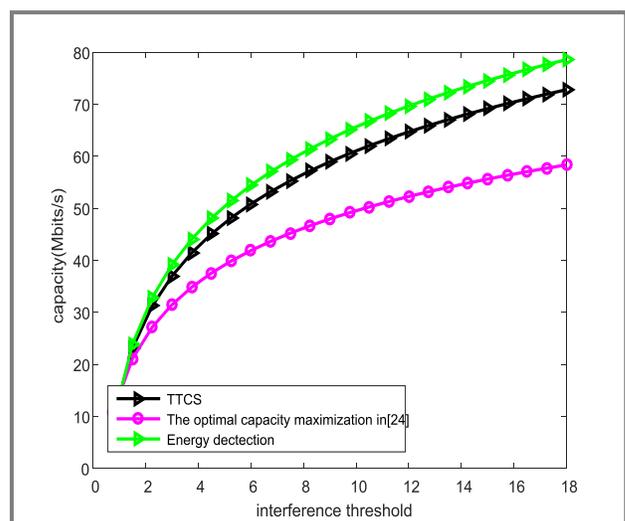


Figure 11: Capacity (M bits/s) versus Interference Threshold

## VI. CONCLUSION

We proposed an EERA method called TTCS based on a two tier GA to maximize the system downlink capacity in overlapping areas where heterogeneous PNETs coexist with multi-RATs. The evaluation results showed that this method had better convergence because it could select good genes for the next population and could operate two-tier crossover after 900 iterations.

The results also proved that the two-tier crossover genetic search scheme could find an optimal resource allocation solution. However, further research is necessary to obtain a converging solution with lower time requirements and lower computational complexity.

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