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Optimal Power Allocation for Green Cognitive Radio using Differential Evolution Approach

K Deepak Raj, Y S S Kaushik, M Siva Kumar
Department of EEE/ENI
BITS Pilani K.K Birla Goa Campus
Goa, India

Abstract— **In this study, the problem of determining the power allocation that maximizes the energy efficiency of cognitive radio network is investigated using differential evolution algorithm with constraint handling technique. The energy-efficient fractional objective is defined in terms of bits per Joule per Hertz. The proposed constrained fractional programming problem is a non-linear non-convex optimization problem. Nature inspired algorithms like Differential Evolution (DE) can describe and resolve complex relationships from intrinsically very simple initial conditions with little or no knowledge of the search space. In simulation results, the effect of different system parameters (interference threshold level, number of primary users and number of secondary users) on the performance of the proposed algorithm is investigated.**

Index Terms—Green cognitive radio, power allocation, energy efficiency, differential evolution

1 INTRODUCTION

Energy efficiency plays a key role in designing wireless communication networks. The energy-efficient wireless networks help in saving the battery life and reduction in global warming. Massive growth and demand of high data rate wireless devices and applications cause significant increase in the greenhouse gas emissions and crowdedness in available frequency spectrum. The main goal of green communication is to develop wireless networks, protocols and devices that jointly maximize the high data rate and minimize the greenhouse gas emissions, that is, minimize the transmit power. The maximum data rate transfer with minimum transmit power is the key of green communication.

Cognitive Radio (CR) is an adaptive, intelligent radio and network technology that can automatically detect available channels in a wireless spectrum and change transmission parameters enabling more communications to run concurrently and improve radio operating behavior. This optimizes the use of available radio-frequency (RF) spectrum while minimizing interference to other users. The main challenge of green cognitive radio is how best a network can allocate power to the wireless devices that can take care of spectrum crowdedness, data rate demand and greenhouse gas emissions.

2 SYSTEM MODEL AND PROBLEM FORMULATION

We consider a wireless network with a base station (BS), K secondary users (SU's) and M primary users (PU's). M PU's can be either wireless devices or geographic regions in which the strength of the cognitive radio signals must be below a specified interference threshold. Transmissions to each SU takes place on a separate, pre-assigned sub channel; and a central controller decides the power level. We denote total static and leakage circuit power of the transmitter by φ, p_k, denotes the source transmit power to serve k^{th} SU, I_m, the interference threshold at the m^{th} PU and h_k, the channel from the source to k^{th} SU. So, the channel gain h is modelled as

$$h = \tilde{h}\, L_o K_o \left(\frac{d_o}{d}\right)^{\alpha} \quad (1)$$

where K_o is a constant that depends on the antenna characteristic and average channel attenuation, d_o is the reference distance for the antenna far field, d is the distance between transmitter and receiver, α is the path loss constant and $\tilde{h}$ is the Rayleigh random variable. The parameter $L_o = 10^{((\tilde{L}_o/10))}$ is log normal shadowing, where $\tilde{L}_o$ is zero mean Gaussian with standard deviation σ. Table 1 presents the summary of notations and symbols used in this paper.

The IEEE WRAN standard consider two schemes to protect PU's from harmful interference. These are spectrum sensing and geo-location-based database schemes. In these schemes, the geographic locations of PU's and SU's are stored in a centralized database. Both PU and SU network have permission to access location database. We assume that the secondary network has both spectrum sensing capability and access privileges to the location database. We also assume that BS can estimate the active PU's channel gains, perhaps via pilot power detection on a regular basis. Fig. 1 shows a typical Cognitive Radio Network. SU's are represented by solid rectangles and PU's by solid triangles. As shown in Fig. 1, each PU has a protected area. Given a distance d_m between the BS and the m^{th} PU and the radius R_m of the protected area of the m^{th}

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Table 1 Notations

Symbol	Definition
K	number of SUs
M	number of PUs
ϕ	static circuit power of the source in the transmit moc
I_m	interference threshold at *m*th PU
ε	maximum tolerance between theoretical optimal anc ε-optimal solution
A	path loss exponent
R_m	*m*th PU protected distance
d_o	reference distance for the antenna far field
D	distance between secondary transmitter and receivei
$\tilde{h}$	rayleigh random variable associated with the *k*th SU
p_k	source transmit power to serve *k*th SU
Γ	SE
Ω	EE
$g_{m,k}$	channel gain between the source and *m*th PU in *k*th SU band
h_k	channel gain between the source and *k*th SU
L_o	log normal shadowing

PU, the channel gain from the source to mth PU in kth SU band is given as

$$g_{m,k} = \tilde{g}_{m,k} L_o K_o \left(\frac{d_o}{d_m - R_m} \right)^{\alpha} \qquad (2)$$

where $g_{m,k}$ is the small scale fading and α is the path loss exponent. For simplicity, throughout this paper and in simulation results we assume that $R_1 = R_2 = \cdots = R_M$. Interference to the PU I_m, is defined as the total aggregated interference power level perceived by any primary receiver m. The parameter I_m, is the noise floor of the PU's. Any perceived power less than I_m will not affect the operations of PU's network.

Our goal is to maximize the EE of the SU's transmissions while meeting the interference constraints because of the PU's. The EE metric we use in this paper is information bits per Joule. We can write the EE maximization problem for cognitive radio as

$$\max_{p} \frac{\sum_{k=1}^{K} \log\left(1 + \left(p_k h_k / N_o\right)\right)}{\phi_o + \sum_{k=1}^{K} P_k} \qquad (3)$$

Subject to

$$\text{C1: } \sum_{k=1}^{K} p_k g_{m,k} \le I_m, \forall m$$

$$\text{C2: } pk \ge 0, \forall k = 1,2,\ldots k$$

In (3), the constraint C1 assures that interference to PU's is less than a specified threshold. For notational simplicity, we denote throughout this paper SE as $\Gamma(p) = \sum_{k=1}^{K} \log\left(1 + \left(p_k h_k / N_o\right)\right)$ and EE as $\Omega(p) = \left(\left(\Gamma(p)\right) / \phi_o + \sum_{k=1}^{K} P_k\right)$. From the EE expression, Ω(p) we can see that the numerator Γ(p) is a concave function and denominator is an affine function of SU's powers.

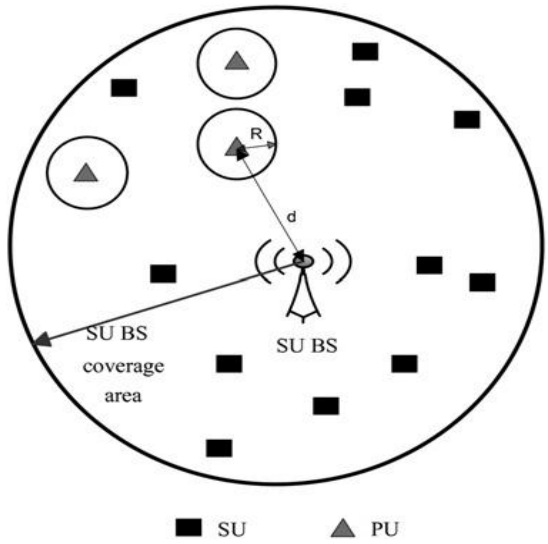

Fig. 1. Cognitive radio system model

Unfortunately, the function Ω(p) is not a concave function of SU's power. We cannot apply standard convex optimization techniques to solve (3).

3 DIFFERENTIAL EVOLUTION (DE)

Differential evolution (DE) is a population based evolutionary algorithm, capable of handling non-differentiable, non-linear and multi-modal objective functions. A brief description of different steps of DE algorithm is given below:

3.1. Initialization

The population is initialized by randomly generating individuals within the boundary constraints,

$X^0_{ij} = X^{min}_j + \text{rand} \times (X^{max}_j - X^{min}_j)$; i = 1, 2, 3 . . . Np;
j = 1, 2, 3 . . . D; (4)

where X^0_{ij} is the initialized jth decision variable of ith population set; 'rand' function generates random values uniformly in the interval [0,1]; Np is the size of the population; D is the number of decision variables. The fitness function is evaluated for every individual and X^{min}_j and X^{max}_j are the lower and upper bound of the jth decision variable, respectively.

3.2. Mutation

As a step of generating offspring, the operations of 'mutation' are applied. 'Mutation' occupies quite a key role in the reproduction cycle. The mutation operation creates mutant vectors X^k_i by perturbing a randomly selected vector X^k_a with the difference of two other randomly selected vectors X^k_b and X^k_c at kth iteration as per following equation.

$X^k_i = X^k_a + F \times (X^k_b - X^k_c)$; i = 1, 2, ...Np (5) where X^k_i is the newly generated i^{th} population set after performing mutation operation at k^{th} iteration; X^k_a, X^k_b and X^k_c are randomly chosen vectors at kth iteration ∈ [i=1, 2, 3, . . .Np] and a≠ b ≠c ≠ i. X^k_a, X^k_b and X^k_c are selected for each parent vectors and F ∈ [0,2] is known as 'scaling factor' used to control the amount of perturbation in the mutation process and improve convergence. Many schemes of creation of a candidate are possible here but strategy 1 has been mentioned in the algorithm.

3.3. Crossover

Crossover represents a typical case of a 'genes' exchange. The parent vector is mixed with the mutated vector to create a trial vector, according to the following equation:

$$X^k_{ij} = \begin{cases} X^k_{ij} & \text{if rand } j < Cr \text{ or } j = q \\ X^k_{ij} & \text{otherwise} \end{cases} \qquad (6)$$

where i=1, 2, 3, . . ., Np; j=1, . . ., D. X^k_{ij}, X^k_{ij}, and X^k_{ij} are the jth individual of ith target vector, mutant vector, and trial vector at kth iteration, respectively. q is a randomly chosen index ∈ (j = 1, 2, . . ., D) that guarantees that the trial vector gets at least one parameter from the mutant vector even if Cr = 0. Cr ∈ [0,1] is the 'Crossover constant' that controls the diversity of the population and aids the algorithm to escape from local optima.

3.4. Selection

Selection procedure is used among the set of trial vector and the updated target vector to choose the best. Each solution in the population has the same chance of being selected as parents. Selection is realized by comparing the objective function values of target vector and trial vector. For minimization problem, if the trial vector has better value of the objective function, then it replaces the updated one as per (7).

$$X^{k+1}_i = \begin{cases} X\_^k_i & \text{if } f(X\_^k_i) \le f(X^k_i) \\ X^k\, i & \text{otherwise} \end{cases} \qquad i = 1, 2, . . . Np \; (7)$$

where X^{k+1}_i is the ith population set obtained after selection operation at the end of kth iteration, to be used as parent population set (in ith row of population matrix) in next iteration (k + 1th).

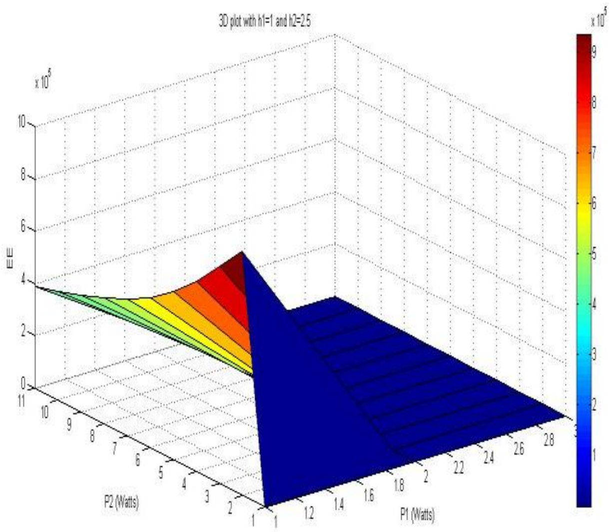

Fig. 2. 3D plot of the objective function with h1 = 1 and h2 = 2.5

4 SIMULATION RESULTS AND DISCUSSION

In this section, we present the simulation results to demonstrate the performance and convergence of the proposed algorithm. The impact of network parameters is also investigated. In all the results, for the SU's channel h, we set do = 20 m, Ko = 50 and α = 3. For PU's channel g, we set do = 1m, Ko = 1 and α = 3. The PU's protected distance Rm is set to 10 m. We also assume that distance d is greater than do. The SU's and PU's are uniformly distributed and the maximum coverage distance of BS is set to 1000 m. The static and leakage circuit power φ is set to 10 − 6 W and for shadowing, we set σ = 10 db.

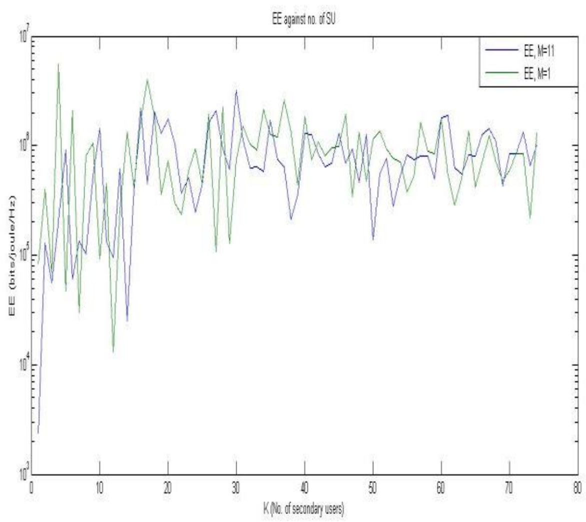

Fig. 3. EE against number of SU plot, M= {1, 11}
The interference threshold of each PU is set to 10 μW

Fig. 3 and 4 presents EE and SE against number of SU's with different number of PU's a satisfy the worst PU. Note that main aim of the objective function is to maximize the EE. We also observe that EE decreases with the increase in number of PU's. In both figures, the parameters are set to M= {1, 11}, Im = 10µW, No=1 µW/Hz. The optimal EE does not always mean minimum power usage. Owing to the structure of the EE optimization objective, a slight increase or decrease in the power will change EE many folds. The results of Fig. 5 confirm these explanations.

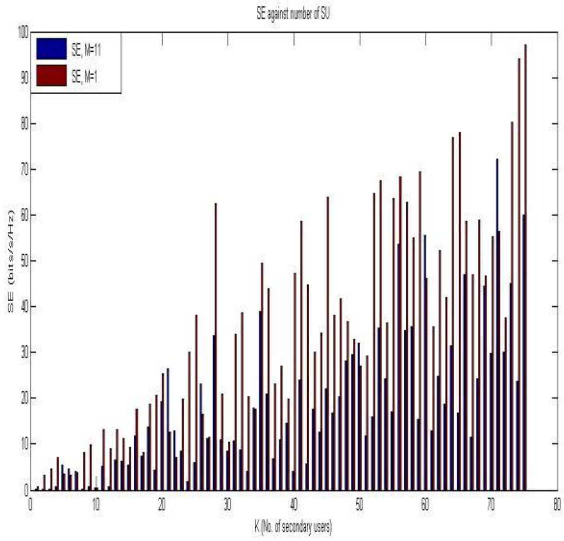

Fig. 4. SE against number of SU plot, M= {1, 11}
The interference threshold of each PU is set to 10 µW

Figs. 5 and 6 present the performance of the proposed differential algorithm with number of iterations for different number of SU's, PU's and interference thresholds.

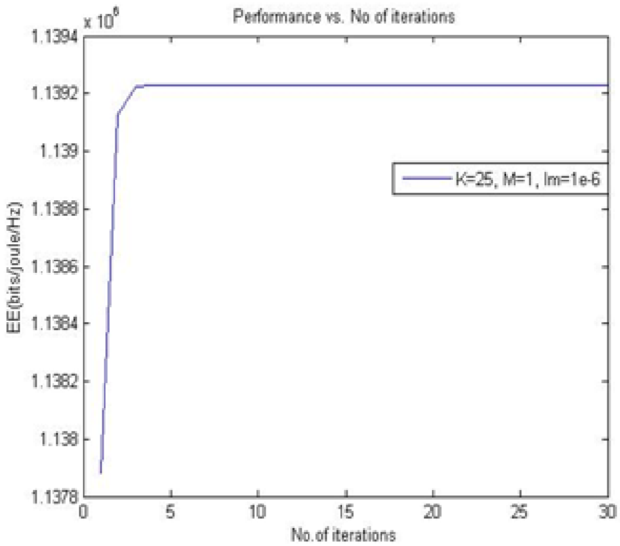

Fig. 5. Performance with number of iterations

In Figs. 5 and 6 the simulations parameters are set to {K, M, Im,} = {25, 1, 1 µW} and {5, 20, 10 µW}, respectively. We can observe that the EE becomes stable in less number of iterations with low interference threshold. We also see that the differential evolution algorithm converges to the optimal solution within ten iterations, for all the different scenarios (different SU's, PU's etc.). From Fig 7, we can observe that transmission power decreases with the number of SU's and the EE increases with the number of SU's.

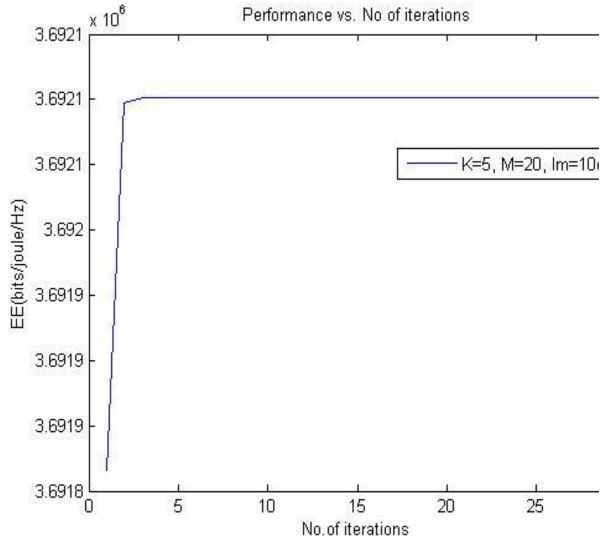

Fig. 6. Performance with number of iterations

This is because with more SU's, there is more freedom in power allocation. We also observe that the EE decreases with the increase in the number of PU's, because the optimization problem has more number of constraints to satisfy.

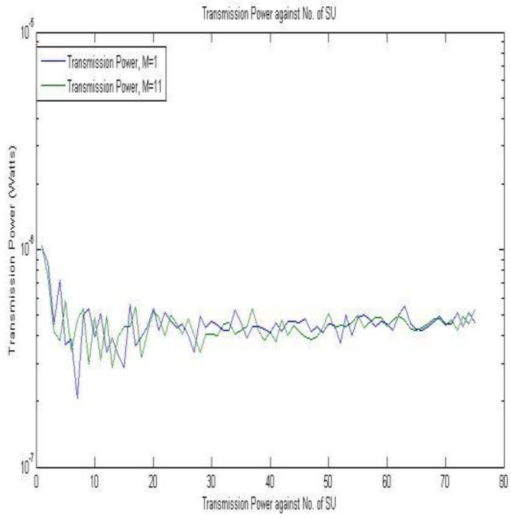

Fig. 7. EE and total transmission power against number of SU plot, M= {1, 11}. The interference threshold of each PU is set to 10 µW

5 CONCLUSIONS

In this paper, an algorithm that employs Differential Evolution (a meta-heuristic search technique), is used to determine the power allocated to each secondary user that maximizes the energy efficiency of the cognitive radio network. The energy-efficient fractional objective is defined in terms of bits per Joule per Hertz. The main advantage of this proposed method is that it systematically decides the power allocation to realize the optimum energy efficiency. The effect of different system parameters (interference threshold level, number of primary users and number of secondary users) on the performance of the proposed algorithm is investigated.

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