Cognitive Radio Parameter Adaptation using Multi-Objective Evolutionary Algorithm

Deepak K. Tosh[1], Siba K. Udgata[1], and Samrat L. Sabat[2]

[1] Department of Computer and Information Sciences
University of Hyderabad, Hyderabad-500046 India
dktosh@gmail.com, udgatacs@uohyd.ernet.in
[2] School of Physics
University of Hyderabad, Hyderabad-500046, India
slssp@uohyd.ernet.in

Abstract. Cognitive Radio (CR) is an intelligent Software Defined Radio (SDR) that can alter its transmission parameters according to predefined objectives by sensing the dynamic wireless environment. In this paper, we propose a method to determine the necessary transmission parameters for a multicarrier system based on multiple scenarios using a multi-objective evolutionary algorithm like Non-dominated Sorting based Genetic Algorithm (NSGA-II). Each scenario is represented by a fitness function and represented as a composite function of one or more radio parameters. We model the CR parameter adaptation problem as an unconstrained multi-objective optimization problem and then propose an algorithm to optimize the CR transmission parameters based on NSGA-II. We compute the fitness score by considering multiple scenarios at a time and then evolving the solution until optimal value is reached. The final results are represented as a set of optimal solutions referred as *pareto-front* for the given scenarios. We performed multi-objective optimization considering two objectives and the best individual fitness values which are obtained after final iteration are reported here as the *pareto-front*.

1 Introduction

Ideally a Cognitive Radio (CR) possesses the capability of sensing, perceiving, decision making, planning, and learning[1] in a wireless environment. Thus CR can alter its transmission parameters to ensure optimal usage of currently available resources, and achieve required Quality of Service (QoS). It alleviates spectrum scarcity problem[2][4] identified by Federal Corporation of Communication (FCC). The cognitive radio must sense the environment periodically and appropriately alter the transmission parameters according to objectives and requirements of the user. This learning characteristic of CR makes it intelligent that adapts itself in dynamic situations.

Though CR has a main goal to improve spectrum utilization efficiency[3], it can also have other goals to achieve; like Bit Error Rate (BER) minimization,

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transmit power minimization, interference minimization, throughput maximization, and spectral efficiency maximization. Therefore, the transmission parameters have to be optimized according to the specified objectives of a user. The tunable transmission parameters of CR are transmission power (P), Modulation Type, Modulation Index (m), Symbol Rate (R_s), Bandwidth (B), Frame Length (L), Time Division Duplex (TDD) in percentage, and Coding Rate (R_c) etc. Many research works have been done on spectrum sensing, allocation as well as parameter adaptation of CR. Dynamic power adjustment schemes have been proposed in [7][8] for wireless systems. For attaining high throughput, adaptive modulation scheme is proposed in [10][11][12]. A set of single carrier and multi-carrier fitness functions have been derived and GA is used to search the optimal set of transmission parameters in [5]. Adaptive transmission in the context of cognitive radio networks is addressed in [17] where GA is used to optimize the CR parameters by considering several QoS and channel coding schemes. A Binary Ant Colony Optimization (BACO) algorithm is used to solve the problem by formulating it into single objective function [13]. Particle Swarm Optimization (PSO) is also being used in [14] to determine the CR parameters for a given set of objectives. It was observed that PSO outperforms GA in terms of convergence speed and consistency. A multi-objective hybrid genetic algorithm (HGA) is used to determine the optimal set of radio transmission parameters for a single carrier CR engine in [9].

All the above works have attempted to solve the parameter adaptation problem in CR by formulating it into single objective functions using weighted sum approach. If a multi-objective optimization problem is solved by weight vector aggregate sum approach the result will find a single value for each parameter and thus the behavior of solution space cannot be deduced with respect to multiple objective functions. For the real-time scenario, the performance of CR system depends on the choice of weights to specific objective functions which is hard and scenario dependent.

A Non-dominated Neighbor Distribution multi-objective genetic algorithm (NNDA) is proposed in [15] which ensures superior individuals are always selected to next generation. The same problem is solved by using multi-objective immune genetic algorithm (MIGA) based on non-dominated sort in [16] and a comparative study with NSGA-II[18] is performed. These works considered two scenarios only; minimization of power and maximization of bit rate. The fitness functions representing two scenarios do not consider parameters like modulation index (m), bandwidth (B), coding rate (R_c) and symbol rate (R_s) which play significant role in achieving QoS. Additionally, there can be more scenarios that must be considered for finding all reconfigurable CR parameters. In our work, we focused to perform a simultaneous optimization of more than one conflicting objectives at a time using Non-dominated Sorting-based Genetic Algorithm (NSGA-II) instead of weighted sum approach. This helps to find a set of optimal solutions from the large range of solution space defined in terms of pareto optimal set. For experimentation, we have performed multi-objective optimization by taking two objectives at a time and best individual fitness values which are obtained after final iteration are reported here as the *pareto-front*.

The rest of the paper is organized as follows. Different radio parameters along with single and multicarrier objective functions are described in section 2. In section 3, the multi-objective approach to the parameter adaptation problem is briefly discussed. The experimental setup for CR adaptation, its analysis and results are reported in section 4. Finally conclusions are drawn in section 5.

2 Problem Definition and Cognitive Radio Objectives

Assuming a multicarrier dynamic wireless environment with N_c subcarriers, the basic characteristic of CR is to sense the environmental parameters, and it learns itself to adjust the value of transmission parameters to achieve the predefined quality of service (QoS). In CR system, the environmental parameters act as input to the problem and the transmission parameters act as decision variables. Hence the problem can be defined as to find the set of transmission parameters by modeling the scenarios as multi-objective functions. The proposed algorithm is based on NSGA-II to solve the formulated multi-objective function to obtain the required solutions. The below subsection briefs about the radio parameters involved in CR engine[5].

2.1 Radio Parameters

Radio parameters of CR are categorized into environmental parameters and transmission parameters. The former gives knowledge of environmental characteristics of multicarrier wireless environment which are used as inputs to the CR system, where different environmental parameters[6] include path loss, noise power, signal-to-noise ratio (SNR) in decibel, spectrum information etc.

Transmission parameters are the tunable parameters of CR system. The CR tunes its transmission knobs to corresponding values from the optimal parameter set. The transmission parameters [6] are listed as: transmit power (P), type of modulation (mod_type) scheme used for the communication, modulation index (m), bandwidth (B), channel coding rate (R_c), size of transmission frame in byte (L), time division duplex in percentage (TDD), and symbol rate (R_s). Modulation Index (m) is defined as the total number of symbols in a modulation scheme and TDD represent the percentage of transmit time.

2.2 Objective Functions

The objective functions guide the CR towards finding a set of optimal solutions. Based on the type of scenario and QoS demand, the CR autonomously chooses a parameter set from the *pareto-front* to work on. In this work five objective functions: Bit-Error-Rate minimization, system throughput maximization, power consumption minimization, spectral interference minimization, and spectral efficiency maximization are considered [6]. In the next subsections, we describe the objective functions in detail.

Minimizing Bit-Error-Rate (BER): The ideal goal of communication system is to maintain received power same as transmit power or in other words to minimize the bit error rate in the communication process. Generally bit error rate depends on several parameters like transmit power (P), modulation type, modulation index (m), bandwidth (B), symbol rate (R_s) and noise power (N). Mathematically, the normalized objective function for minimizing BER [6] is defined as

$$f_{min\_ber} = 1 - \frac{log_{10}(0.5)}{log_{10}\bar{P}_{be}} \tag{1}$$

Where $\bar{P}_{be}$ is the mean BER probability for N_c subcarriers. The probability of bit error rate (P_{be}) [19] which is dependent on type of modulation scheme and modulation index (m), can be computed as
In case of BPSK modulation,

$$P_{be} = Q(\sqrt{\gamma}) \tag{2}$$

For m-ary PSK modulation,

$$P_{be} = \frac{2}{log_2(m)} Q(\sqrt{2 * log_2(m) * \gamma} * sin\frac{\pi}{m}) \tag{3}$$

For m-ary QAM modulation,

$$P_{be} = \frac{4}{log_2(m)}(1 - \frac{1}{\sqrt{m}})Q(\sqrt{\frac{3 * log_2(m)}{m-1} * \gamma}) \tag{4}$$

Where $Q(x)$ represents the Q-function in terms of error function. The energy per bit (γ) is expressed as

$$\gamma = \frac{E_b}{N_0} = 10log_{10}\left[\frac{P}{N}\right] + 10log_{10}\left[\frac{B}{R_s * m}\right](dB) \tag{5}$$

Maximizing Throughput: By definition, throughput is defined as the amount of correct information received at the receiver. Maximizing throughput is a common aim in the multimedia environment. Determining the theoretical throughput depends on the parameters such as bandwidth (B) in use, coding rate (R_c), modulation index (m), frame size (L), probability of BER (P_{be})and percentage of transmit time (TDD). The normalized objective function for maximizing throughput [6] for N_c subcarriers is defined as

$$f_{max\_tp} = \frac{\sum_{i=1}^{N_c} \frac{L_i}{L_i+O+H} * (1 - P_{be_i})^{L_i+O} * R_{c_i} * TDD_i}{N_c} \tag{6}$$

Where, O is physical layer overhead and H is MAC and IP layer overhead. Subscript i refers to i^{th} subcarrier of the multicarrier system.

Minimizing Power Consumption: Energy is the most important factor which must be spent optimally for the communication process. Hence minimum power should be consumed for all the tasks while communicating or computing. The parameters contribute to the fitness for power minimization are bandwidth (B), modulation type, coding rate (R_c), time division duplexing (TDD), symbol rate (R_s) and transmit power (P). The normalized objective function for minimizing power [6] is expressed as

$$f_{min\_power} = 1 - \Bigg[\alpha * \frac{\sum_{i=1}^{N_c}(P_{max} + B_{max}) - (P_i + B_i)}{N_c * (P_{max} + B_{max})} + \beta * \frac{\sum_{i=1}^{N_c} log_2(m_{max}) - log_2(m_i)}{N_c * log_2(m_{max})} + \lambda * \frac{\sum_{i=1}^{N_c} R_{s_{max}} - R_{s_i}}{N_c * R_{s_{max}}}\Bigg] \quad (7)$$

Where, α, β, and λ represents weighting factors of the objective function. Subscript i refers to i^{th} subcarrier of the multicarrier system.

Minimizing Spectral Interference: Interference is caused due to simultaneous transmissions by multiple users in the same spectrum band. So it affects throughput as well as bit error rate of the communication system. To achieve high throughput with less error rate, minimization of spectral interference is necessary. Transmission parameters such as transmit power (P), bandwidth (B) and time division duplexing (TDD) are used to determine the approximate amount of spectral interference fitness value. The normalized objective function for minimizing interference [6] is represented as:

$$f_{min\_si} = 1 - \frac{\sum_{i=1}^{N_c}((P_i * B_i * TDD_i) - (P_{min} * B_{min} * 1))}{N_c * (P_{max} * B_{max} * 100)} \quad (8)$$

Maximizing Spectral Efficiency: Spectral efficiency can be defined as the amount of information that can be transmitted over a given bandwidth. The symbol rate (R_s) and modulation index (m) are used to determine the total amount of information being transmitted. To maximize the spectral efficiency, high amount of information is needed in small bandwidth. The normalized objective for maximizing spectral efficiency [6] is expressed as

$$f_{max\_se} = \frac{\sum_{i=1}^{N_c} \frac{m_i * R_{s_i} * B_{min}}{B_i * m_{max} * R_{s_{max}}}}{N_c} \quad (9)$$

In the above expressions, parameter with subscript max and min represent the maximum and minimum value of that parameter respectively defined in table 1.

3 Multi-Objective Approach for Parameter Adaptation

In general, a multi-objective optimization problem is to determine the optimal value of a set of solutions ($\overrightarrow{x}$) while optimizing a set of k conflicting objectives

Algorithm 1 CR_PARAMETER_ADAPTATION

Input: Environmental sensing information
Output: Set of optimal transmission parameters

Define all the objective functions and search range for the radio parameters
for all distinct combinations of two objective functions **do**
  Extract the environment parameters from sensed information of wireless environment.
  Initialize the population P (Transmission Parameters) with uniform random numbers in a given search range.
  while Stopping criteria is not met or Required accuracy is not reached **do**
    Find out the optimal solution set by performing multi-objective optimization using NSGA-II.
  end while
  Plot the obtained optimal solution as *pareto-front* and record the transmission parameter values for CR adaptation.
end for

simultaneously. Mathematically, the multi-objective unconstrained optimization problem is defined as

$$\begin{aligned}
&\text{Find } \overrightarrow{x} = (x_1, x_2, x_3, \cdots, x_D) \\
&\text{that optimizes } \langle f_1(\overrightarrow{x}), f_2(\overrightarrow{x}), \cdots, f_k(\overrightarrow{x})\rangle \\
&\text{with } l_i \le x_i \le u_i,\ i = 1, 2, \cdots, D
\end{aligned}$$

In the above formulation, $\overrightarrow{x}$ is the decision variable with X as parameter space and $\overrightarrow{y}$ is the set of objectives with Y as objective space; k is the number of objectives, D is the number of decision variables in the problem. l_i and u_i defines the lower and upper bounds of defining x_i, the search space of D-distinct radio parameters. The CR adaptation problem can be modeled as a multi-objective optimization problem which is defined in following

$$\begin{aligned}
&\text{Find } \overrightarrow{x} = \langle P, mod_type, m, B, R_c, L, TDD, R_s\rangle \\
&\text{that minimizes,} \\
&\big\langle f_{min_ber}(\overrightarrow{x}), f'_{min_tp}(\overrightarrow{x}), f_{min_power}(\overrightarrow{x}), f_{min_si}(\overrightarrow{x}), f'_{min_se}(\overrightarrow{x})\big\rangle \\
&\text{where } f'_{min_tp}(\overrightarrow{x}) = -f_{max_tp}(\overrightarrow{x}) \\
&\text{and } f'_{min_se}(\overrightarrow{x}) = -f_{max_se}(\overrightarrow{x})
\end{aligned}$$

The proposed algorithm 1 finds out the optimal transmission parameters and pareto optimal front, considering two objectives at a time. Initially, all the objective functions have to be defined which return the fitness score based on a single parameter set and the feasible search range must be specified. For all distinct combinations of two objective functions, we compute the fitness score for population size P and performed NSGA-II that evolves the solution until optimal value is reached. The final results obtained are referred as *pareto-front* for the two scenarios taken.

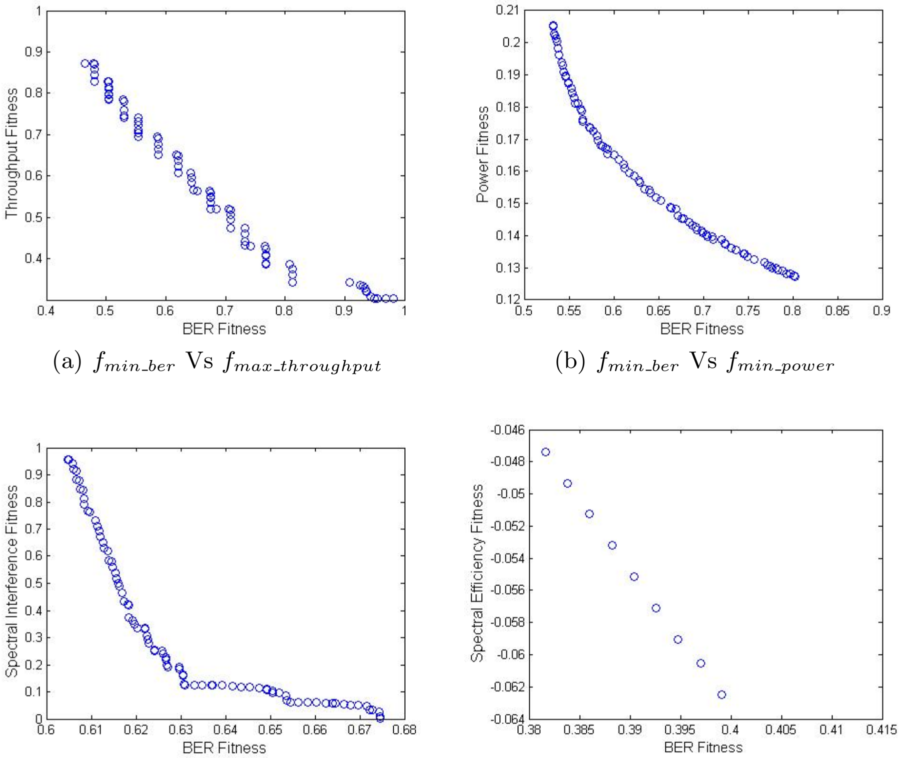
4 Simulation Setup and Results

We simulated the above mentioned multi-objective problem using Non-dominated Sorting based Genetic Algorithm (NSGA-II) in Matlab. We tried to address the problem by taking two conflicting objectives at a time and perform the optimization by assuming 16 subcarriers in the CR network. The parameter list with their labels and range of values are shown in the table 1. A population size of 100 and iterations of 1500 is considered during simulation. To obtain an optimal front, both objective functions need to be conflicting with each other, that means there should be some common parameters that guide both fitness functions towards optimality. As all the fitness functions are not linear, the nature of front can be nonlinear as well as discrete. We have taken all possible distinct combinations by taking two objectives at a time. The best individual fitness values which are obtained after final iteration are reported as the pareto set best described using *pareto-front* as in figures 1–3.

Table 1: Transmission Parameters with their Ranges

$Parameter(x)$	x_{min}	x_{max}
Transmit Power (P)	1 dBm	18 dBm
Modulation Index (m)	2	128
Bandwidth (B)	2 MHz	32 MHz
Coding Rate (R_c)	1/2	3/4
Frame Length (L)	94 Bytes	1504 bytes
Time Division Duplex (TDD)	1%	100%
Symbol Rate (R_s)	125 Ksps	1 Msps
Noise Power (N)	-30 dBm	-5 dBm

The pareto optimal fronts obtained by taking BER minimization fitness and one from all other fitness functions is shown in figure 1. In the figure 1(a) represents the *pareto-front* between fitness for minimizing BER and maximizing throughput. The probability of BER (P_{be}) is a common parameter in Eq. 1 and 6 . It can be inferred from the equations that if P_{ber} increases then f_{min_ber} and f'_{min_tp} increases. Hence f_{min_ber} and f_{max_tp} exhibit an inverse relationship which is depicted in the figure 1(a). In figure 1(b) the typical nature of minimization of BER and power fitness is depicted. In practice, if transmit power (P) decreases, then probability of BER increases. Hence the f_{min_ber} in Eq. 1 increases where as the f_{min_power} in Eq. 7 decreases. Figure 1(c) shows optimal pareto-front between fitness for BER minimization (Eq. 1) and fitness for interference minimization (Eq. 8). In both fitness functions, power (P), symbol rate (R_s), modulation index (m) and bandwidth (B) are the common parameters which affect bit error rate and interference fitness. The f_{min_si} decreases with increase in f_{min_ber}. The optimal *pareto-front* for fitness of BER minimization (Eq. 1) and spectral efficiency maximization (Eq. 9) is shown in figure 1(d). As



(a) f_{min_ber} Vs $f_{max\_throughput}$

(b) f_{min_ber} Vs f_{min_power}

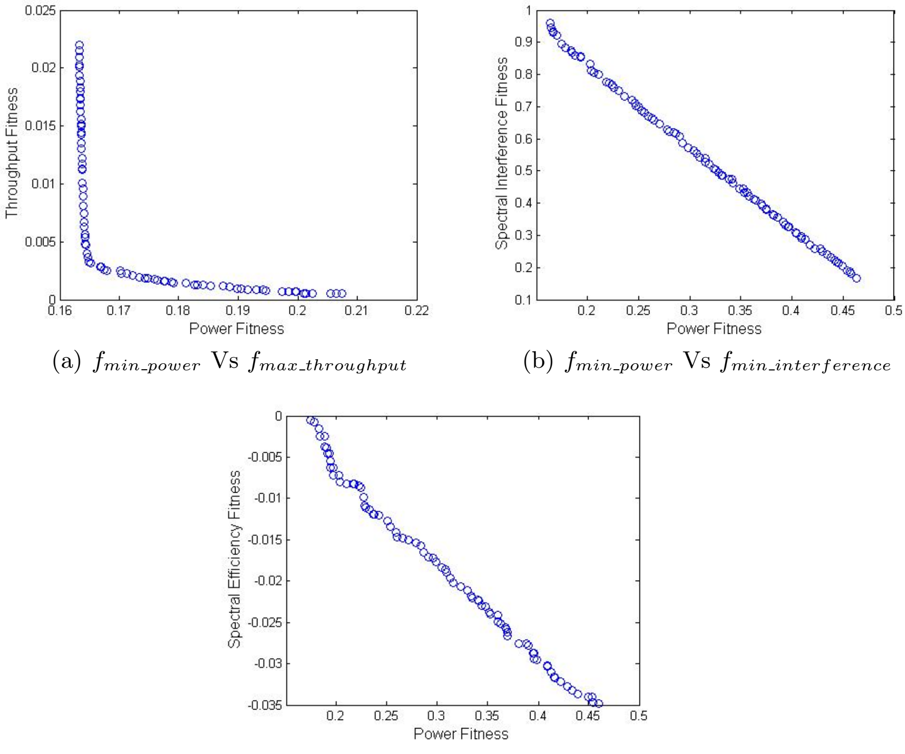
(c) f_{min_ber} Vs $f_{min\_interference}$

(d) f_{min_ber} Vs $f_{max\_spec\_efficiency}$

Fig. 1: *Pareto-front* obtained with respect to fitness for BER minimization

f'_{min_si} depends on modulation index (m), symbol rate (R_s) and bandwidth (B), so P_{be} is the common factor for f_{min_ber} and f'_{min_se}. Thus, both fitness functions are inversely related to each other due to the parameter P_{be}.

The pareto optimal fronts obtained by taking fitness for interference minimization and one from all other fitness functions without any repetition, is shown in figure 2.The *pareto-front* between minimizing power fitness (Eq. 7) and maximizing throughput fitness (Eq. 6) is shown in figure 2(a). The nature of the plot shows through f_{max_tp} is decreasing with increase in f_{min_power}. Then we have plotted the front between fitness for power minimization (Eq. 7) and fitness for interference minimization (Eq. 8) in figure 2(b). The common parameters between these two functions are power (P), bandwidth (B). If values of both parameters increase, then f_{min_si} decreases and f_{min_power} increases. The front is likely to be linear as both functions are linear. In figure 2(c), we have plotted the front between fitness of power minimization (Eq. 7) and fitness for spectral



(a) f_{min_power} Vs $f_{max\_throughput}$

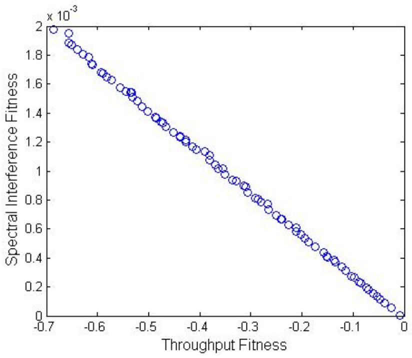
(b) f_{min_power} Vs $f_{min\_interference}$

(c) f_{min_power} Vs $f_{max\_spec\_efficiency}$

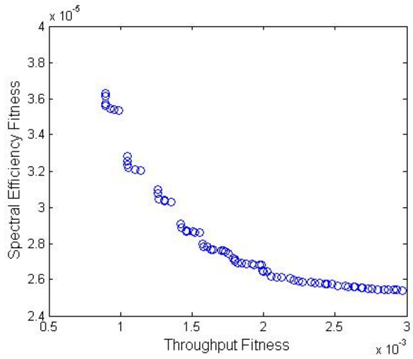
Fig. 2: *Pareto-front* obtained with respect to fitness for power minimization

efficiency maximization (Eq. 9). In this case symbol rate (R_s), modulation index (m) and bandwidth (B) play important role to find out the *pareto-front*.

The pareto optimal fronts obtained by taking fitness for throughput maximization and one from all other fitness functions without any repetition is shown in figure 3. Figure 3(a) represents the optimal front between fitness of interference minimization (Eq. 8) and fitness for throughput maximization (Eq. 6). With decrease in power value, f_{min_si} and probability of bit error rate (P_{be}) increases. f'_{min_tp} value decreases with decrease in P_{be}. This indicates the inverse relationship between the two functions. Figure 3(b) represents the front by taking fitness for throughput maximization (Eq. 6) and spectral efficiency maximization (Eq. 9). As P_{be} and energy per bit (γ) depends on m, B, and R_s; so f_{max_se} and f_{max_tp} are dependent on these parameters. With increase in f_{max_tp}, P_{be} decreases and γ increases keeping other parameters constant. Thus the value of f_{max_se} decreases with increase in f_{max_tp} which is depicted in figure 3(b).

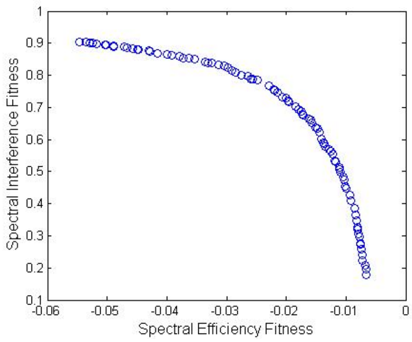


(a) $f_{max\_throughput}$ Vs $f_{min\_interference}$



(b) $f_{max\_throughput}$ Vs $f_{max\_spec\_efficiency}$

Fig. 3: *Pareto-front* obtained with respect to fitness for throughput maximization



(a) $f_{max\_spec\_efficiency}$ Vs $f_{min\_interference}$

Fig. 4: *Pareto-front* obtained with respect to fitness for interference minimization

At last, in figure 4(a), we have plotted the front between fitness for maximizing spectral efficiency (Eq. 9) and minimizing interference fitness (Eq. 8). As f_{min_si} value increases with decrease in transmission power (P), it results decrease in γ value. Hence f'_{min_se} gradual decreases with increase in f_{min_si}.

5 Conclusions and Future Work

In this work, we modeled the Cognitive Radio parameter adaptation in dynamic spectrum allocation as a multi-objective optimization problem. NSGA-II algorithm is used to solve the problem. The different solution set obtained from the *pareto-front* can be used in the decision model for parameter tuning. To the best of our knowledge this is the first attempt to approach the decision model as a multi-objective optimization problem. The set of solutions obtained through the multi-objective solution approach helps us to get an insight to the problem and to obtain a set of solutions. This probably helps the cognitive radio engine to take the best decision based on requirement, availability and trade-off. In this phase of work we tried to find optimal *pareto-front* by considering only two scenarios. But in practice, there can be more constraints in real field. For example, some user may want a high throughput and error-free communication with minimum power consumption. Hence for this case, we should consider more than two objectives and optimize them to find optimal solution set. The resulting solution set will help to analyze the nature and behavior of the solution space.

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