DYNAMIC RESOURCE ALLOCATION ALGORITHMS FOR COGNITIVE RADIO SYSTEMS

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Under the guidance of **Prof. Poonam Singh**

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CERTIFICATE

This is to certify that the thesis entitled "**Dynamic Resource Allocation Algorithms for Cognitive Radio Systems**" submitted by **Mr. Varun Subramanian** and **Mr. Swaraj Rimal** for partial fulfilment for the requirement of Bachelor in Technology degree in **Electronics and Communication Engineering** at National Institute of Technology, Rourkela is an authentic piece of work carried out by them under my guidance and supervision.

To the best of my knowledge, the matter in this thesis has not been submitted to any other University / Institute for the award of any Degree.

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Date:

Table of Contents

1. Abstract

Cognitive Radio (CR) is a novel concept for improving the utilization of the radio spectrum. This promises the efficient use of scarce radio resources. Orthogonal Frequency Division Multiplexing (OFDM) is a reliable transmission scheme for Cognitive Radio Systems which provides flexibility in allocating the radio resources in dynamic environment. It also assures no mutual interference among the CR radio channels which are just adjacent to each other. Allocation of radio resources dynamically is a major challenge in cognitive radio systems. In this project, various algorithms for resource allocation in OFDM based CR systems have been studied. The algorithms attempt to maximize the total throughput of the CR system (secondary users) subject to the total power constraint of the CR system and tolerable interference from and to the licensed band (primary users). We have implemented two algorithms Particle Swarm Algorithm(PSO) and Genetic Algorithm(GA) and compared their results.

1. Introduction

1.1. Cognitive Radio

With the development of wireless devices and technology, new frequency bands are being used in the radio spectrum. Due to increase in the wireless device count, the radio spectrum is becoming increasingly congested. Also, the augmentation in the new wireless devices with the development in technology has promised more and more frequency band to be utilized. This may result in the high level of interference among the frequency bands which are being operated adjacent to each other. Again, it depends on the time and place of use. However, if trend continues in the future, all the remaining frequency bands will be utilized and the devices need to face heavy interference thus restricting the performance. This may lead to deciding of the upper limit to the wireless device count.

Measurements and statistics show that a broad range of the spectrum is not being used all the time, depending on the geographical region, whereas the other ranges are used heavily. Thus, the radio spectrum is being underutilized depending on the place and time of the day. This results in the inefficient use of the spectrum. Generally, the frequency bands which are licensed operate at fixed time and remaining time they are free. These free or unused bands of the spectrum cannot be used by conventional wireless systems because these are licensed and can be used only by the respected owners of that band. So, to use those bands which are unused by the licensed user during certain time, we need a device which can automatically change the operating parameters whenever it senses the unused band.

Cognitive Radio also known as smart radio is an intelligent radio technology which can learn its radio environments and change its transmission parameters [3]. It was first proposed by Joseph Mitola in a seminar at KTH, The Royal Institute of Technology, in

1998. So, Cognitive Radio is sometimes referred to as Mitola Radio. It can adapt itself to decide the future actions dynamically to improve the communication quality and meet the overall requirements of the users. The main feature of CR system is that it is autonomous and is software controlled. It can change its characteristics dynamically without the intervention of the user. This involves the sensing of the free spectrum and then deciding the radio resources such as bandwidth, symbol rate, power, number of subcarriers etc. to a group of secondary (or CR) users based on the behavior of the users to whom the frequency band is licensed (primary users). These processes are all controlled by software and are fully dynamic in nature.

The main functions of Cognitive Radio are to sense the environment, to manage the environment for data transfer, to look for any disturbances in the environment and if so, then re-sense the environment for nominal disturbances. It operates in a cycle fashion such that it begins sensing the environment unless it is not favorable for data transmission. Here, sensing the environment means sensing the free and unused band of frequency.

The spectrum sensing involves the detection of unused spectrum from the wireless band which results in minimal interference with other users. The free frequency bands are known as spectrum holes. There are various techniques by which the spectrum holes can be detected such as Transmitter detection, Matched Filter detection, Energy detection, etc. After the proper frequency has been sensed, the problem of spectrum management arrives. It requires the allocation of various parameters on which data transmission takes place. It includes allocation of proper subcarriers, transmit power, number of bits per symbol, all within the interference level of the adjacent band of another user and proper quality of service. If the operating channel meets with the interference level above threshold, them the frequency of operation needs to be changed in a smooth manner, not disrupting the existing data exchange.

1.2. OFDM for Cognitive Radio

OFDM stands for Orthogonal Frequency Division Multiplexing. It is the multi-carrier modulation technique in which data is split up into chunks and every chunk are modulated using closely spaced orthogonal subcarriers. The orthogonal subcarriers have the property that they do not have any mutual interference between them. So, this scheme is very useful for high bit-rate data communication. One of the serious problems of high data rate transmission is time dispersion of pulses resulting in Inter-symbol Interference (ISI). In OFDM, the data is split into several low-rate data chunks and are modulated in overlapping orthogonal subcarriers. These splitting increases the symbol duration by the number of subcarriers used, thus reducing the ISI due to multipath.

OFDM is adapted as the best transmission scheme for Cognitive Radio systems [3]. The features and the ability of the OFDM system makes it fit for the CR based transmission system. OFDM provides spectral efficiency, which is most required for CR system. This is because the subcarriers are very closely spaced and are overlapping, with no interference. Another advantage of OFDM is that it is very flexible and adaptive. The subcarriers can be turned on and off according to the environment and can assist CR system dynamically. OFDM can be easily implemented using the Fast Fourier Transform (FFT), which can be done by digital signal processing using software.

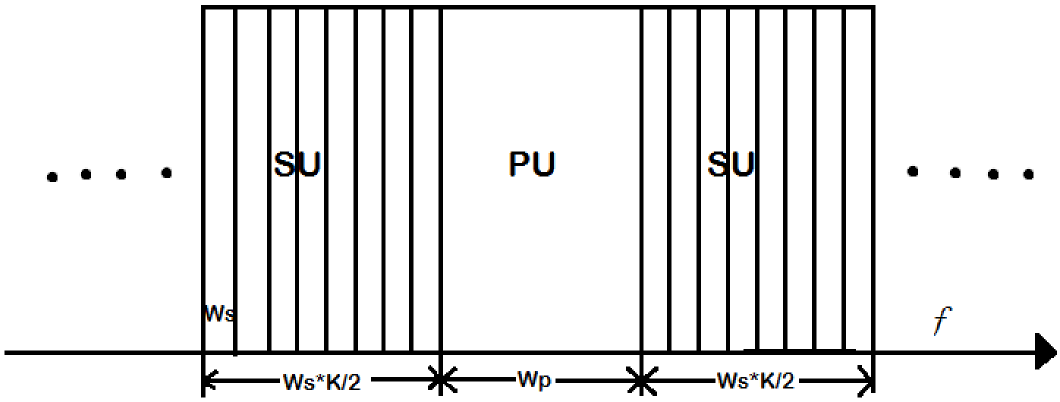
1.3. Objective

The main objective of this project is to write optimal algorithms to dynamically allocate the radio resources to the Cognitive Radio systems which can maximize the throughput of the system within the power and interference constraints provided by the alongside operating primary users and total power of the CR system.

2. Fair Adaptive algorithm

The Fair Adaptive allocation algorithm is based on the fairness in allocation bit rates for each secondary user in the CR system. This algorithm is fair in the sense that it tries to allocate bits to users who have not received their fair share of service as much as possible [1]. The algorithm first allocates bits to users to ensure fairness, and then subcarrier and power are decided in greedy manner.

2.1. System Model [1]



We have assumed a system consisting of base station which serves both primary and secondary users. Let us consider *M* secondary users are operating in the CR system in the vicinity of only one primary or licensed user. The primary and secondary users have adjacent frequency bands. The bandwidth of the primary user band is *Wp* Hz and that of secondary sub-band is *Ws* Hz. We assume the presence of *K* orthogonal subcarriers such that *K/2* subcarriers are present in either side of the primary band. Hence the total bandwidth of the CR system is *Ws*K/2* Hz. Since orthogonal subcarriers have no interference, only interference due to primary and secondary users has been considered.

The power spectral density (PSD) of k^{th} subcarrier signal is assumed to be:

$$\Phi_k(f) = P_k T_s \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2 \qquad (1)$$

where,

P_k is the transmit power of k^{th} subcarrier

T_s is the symbol duration

Let I_k be the interference power introduced by the secondary signal into the primary band.

So,

$$I_k(d_k, P_k) = \int_{d_k - Wp/2}^{d_k + Wp/2} |g_k|^2 \Phi_k(f) df = P_k IF_k \qquad (2)$$

where,

g_k is the channel gain from base station to primary user for k^{th} subcarrier

d_k is the spectral distance between k^{th} subcarrier and primary band

IF_k is the interference factor for k^{th} subcarrier

Let S_{mk} be the interference power introduced by primary signal into k^{th} secondary band at m_{th} user. So,

$$S_{mk}(d_k) = \int_{d_k - Ws/2}^{d_k + Ws/2} |h_{mk}|^2 \Phi_{RR}\left(e^{j\omega}\right) d\omega \qquad (3)$$

where,

h_{mk} is subcarrier *k* gain from base station to user *m*

$\Phi_{RR}\left(e^{j\omega}\right)$ is the PSD of primary user's signal

Now, maximum number of bits in a symbol transmitted in the k^{th} subcarrier is given by:

$$b_{mk} = \left\lfloor \log_2 \left(1 + \frac{|h_{mk}|^2 P_{mk}}{\Gamma(NoWs + S_{mk})}\right)\right\rfloor \qquad (4)$$

where,

$\lfloor . \rfloor$ denotes the floor function

No is the one sided noise PSD

P_{mk} is the transmit power allocated to k^{th} subcarrier of m^{th} user

Γ is set to unity for simplicity

a_{mk} ϵ (0,1) is a subcarrier allocation indicator. $a_{mk} = 1$ if k^{th} subcarrier is allocated to m^{th} user.

The main objective is to maximize the total bit rate for secondary users constrained by total transmit power, fairness and interference levels. So, the optimization problem can be expressed as:

$$\max Ws = \sum_{m=1}^{M} \sum_{k=1}^{K} a_{mk} b_{mk}$$

where,

$$a_{mk} \in \{0,1\}$$

$$\sum_{m=1}^{M} a_{mk} \leq 1$$

$$P_{mk} \geq 0$$

$$\sum_{m=1}^{M} \sum_{k=1}^{K} a_{mk} P_{mk} \leq P_{total}$$

$$\sum_{m=1}^{M} \sum_{k=1}^{K} a_{mk} P_{mk} IF_k \leq I_{th}$$

P_{total} is the total CRU power

I_{th} is primary user's maximum tolerable interference level

The nominal bit rate weight (NBRW) for m^{th} user is denoted by λ_m so that ($\lambda_m / \sum_{i=1}^{M} \lambda_i$) is the fraction of total secondary user bits loaded to be fairly allocated to user *m*.

2.2. Algorithm [1]

Since the optimal solution for the algorithm is computationally complex and time consuming, which is not suitable for wireless communication, suboptimal approach have been used. The algorithm called Reduced Complexity algorithm has been used where a measure for relative importance of power needed to transmit to secondary users versus interference power introduced to primary user is determined. Then it is used to determine which subcarrier to select, having maximum power, or having minimum interference (k_p or k_i). First, a minimum power algorithm (MP) is used to determine interference power I_{MP} to primary user band; we choose the subcarrier which minimizes the incremental power needed for secondary user. Similarly, minimum interference algorithm (MI) is used to determine total power P_{MI} required to transmit to secondary users for each bit loading. Subcarrier is chosen which minimizes the incremental interference power introduced to primary band.

The incremental power required for transmitting one bit to user m on subcarrier k is given by:

$$\Delta P_{mk} = \frac{NoWs + S_{mk}}{|h_{mk}|^2} 2^{b_{mk}} \qquad (5)$$

The incremental interference power generated by such a transmission is given by:

$$\Delta I_{mk} = P_{mk}\, IF_k \qquad (6)$$

3.2.1. Algorithm (MP)

1) a) $P = 0$, $I_{MP} = 0$.

   b) $B_m = 0$ for $m = \{1, 2, ..., M\}$.

   c) $b_{mk} = 0$; calculate ΔP_{mk} as in (v)

2) a) $m^* = \arg\min_m B_m/\lambda_m$

   b) $k_P = \arg\min_k \Delta P_{m^* k}$

c) If ($P + \Delta P_{m^*kp} < P_{total}$), then

$B_{m*} = B_{m*}+1$, $P = P+\Delta P_{m^*kp}$,

$I_{MP} = I_{MP} + \Delta P_{m^*\,kp}\, IF_{kp}$,

$b_{m^*kp} = b_{m^*kp} + 1$, calculate $\Delta P_{m^*\,kp}$ as in (v),

go to step 2a).

d) If ($P + \Delta P_{m^*kp} > P_{total}$), then set m* to be the user with the next higher value of B_m/λ_m and go to step 2b). Stop if all users have been considered.

3.2.2. Algorithm (MI)

1) a) $P_{MI} = 0$, $I = 0$.

b) $B_m = 0$ for m = {1, 2,..., M}.

c) $b_{mk} = 0$; calculate ΔI_{mk} as in (vi)

2) a) $m^* = \arg\min_m B_m/\lambda_m$

b) $k_I = \arg\min_k \Delta I_{m^*\,k}$

c) If ($I + \Delta I_{m^*kI} < I_{th}$), then

$B_{m*} = B_{m*}+1$, $I = I+\Delta I_{m^*kI}$,

$P_{MI} = P_{MI} + \Delta I_{m^*\,kI} / IF_{kI}$,

$b_{m^*kI} = b_{m^*kI} + 1$, calculate $\Delta I_{m^*\,kI}$ as in (v),

go to step 2a).

d) If ($P + \Delta P_{m^*kp} > P_{total}$), then set m* to be the user with the next higher value of B_m/λ_m and go to step 2b). Stop if all users have been considered.

Now, calculate, $VP = \frac{P_{MI} - P_{total}}{P_{toal}}$ and $VI = \frac{I_{MP} - I_{th}}{I_{th}}$

3.2.3. Algorithm (RC)

1) a) $P = 0$, $I = 0$, $B_m = 0$ for $m = \{1, 2,..., M\}$, $b_{mk} = 0$

b) calculate ΔP_{mk} as in (v) and ΔI_{mk} as in (vi)

2) a) $m^* = \arg\min_m B_m/\lambda_m$

b) $k_P = \arg\min_k \Delta P_{m^*k}$

c) $k_I = \arg\min_k \Delta I_{m^*k}$

d) $X = \frac{VI\,(\Delta P_{m*kp}\, IF_{kp} - \Delta I_{m*kI})}{\Delta I_{m*kI}}$, $Y = \frac{VP\left(\frac{\Delta I_{m*kI}}{IF_{kI}} - \Delta P_{m*kp}\right)}{\Delta P_{m*kp}}$

e) If ($X \geq Y$), set $k^* = k_I$; else set $k^* = k_P$

f) If ($P + \Delta P_{m^*k^*} < P_{total}$) and ($I + \Delta I_{m^*k^*} < I_{th}$) then

$B_{m^*} = B_{m^*}+1$, $P = P+\Delta P_{m^*k^*}$, $I = I+\Delta I_{m^*k^*}$

$b_{m^*k^*} = b_{m^*k^*} + 1$, calculate $\Delta P_{m^*k^*}$, $\Delta I_{m^*k^*}$as in (v, vi),

go to step 2a).

g) else, set m* to be the user with the next higher value of B_m/λ_m and go to step 2b). Stop if all users have been considered.

Number of bits allocated to secondary users is given by:

$$\sum_{m=1}^{M} B_m$$

The complexity of RC algorithm is O(num_bits x K) where num_bits is the total number of loaded bits. So, the computation time is not very high.

2.3. Simulation and Results

2.3.1. Parameters used

- Number of users (M) = 4,
- Number of subcarriers (K) = 8
- Bandwidth of primary band (Wp) = 0.315 MHz
- Bandwidth of secondary band (Ws) = 0.315 MHz,
- Symbol rate (Ts) = 4μs,
- Noise power (No) = 10^{-8} W/Hz
- All channels are Rayleigh distributed random variables with mean = 1
- PSD of primary and secondary signal are same
- Total power budget (P_{total}) = 10 W,

2.3.2. Graphs of maximum bit rate (Rs) v/s Interference threshold (I_{th})

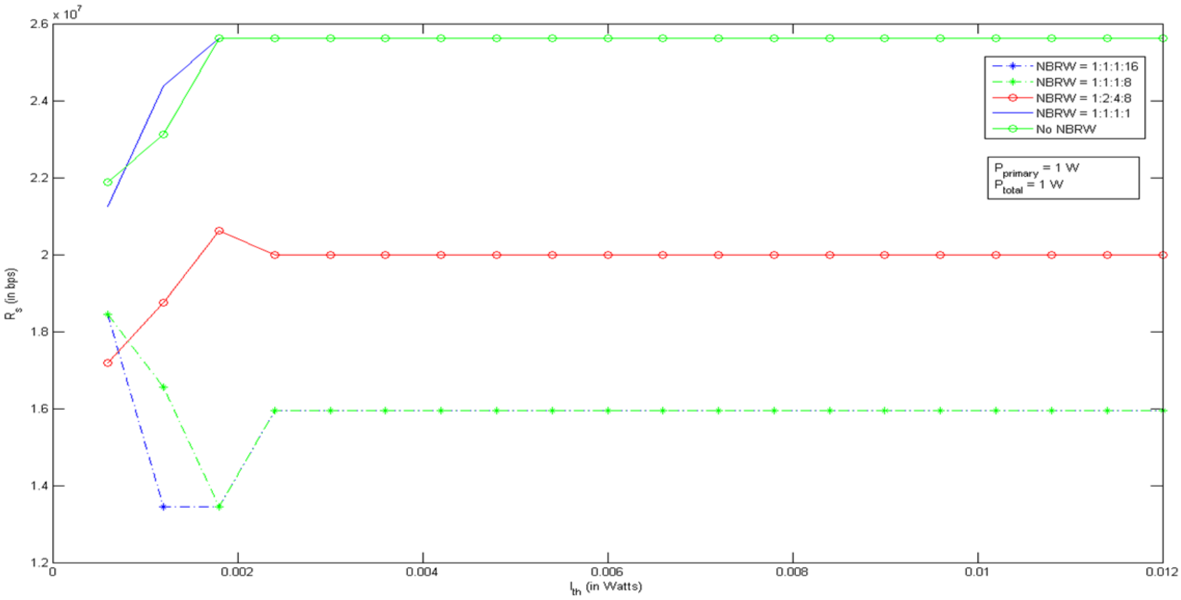


Fig. Plot of Rs v/s I_{th} for different NBRW

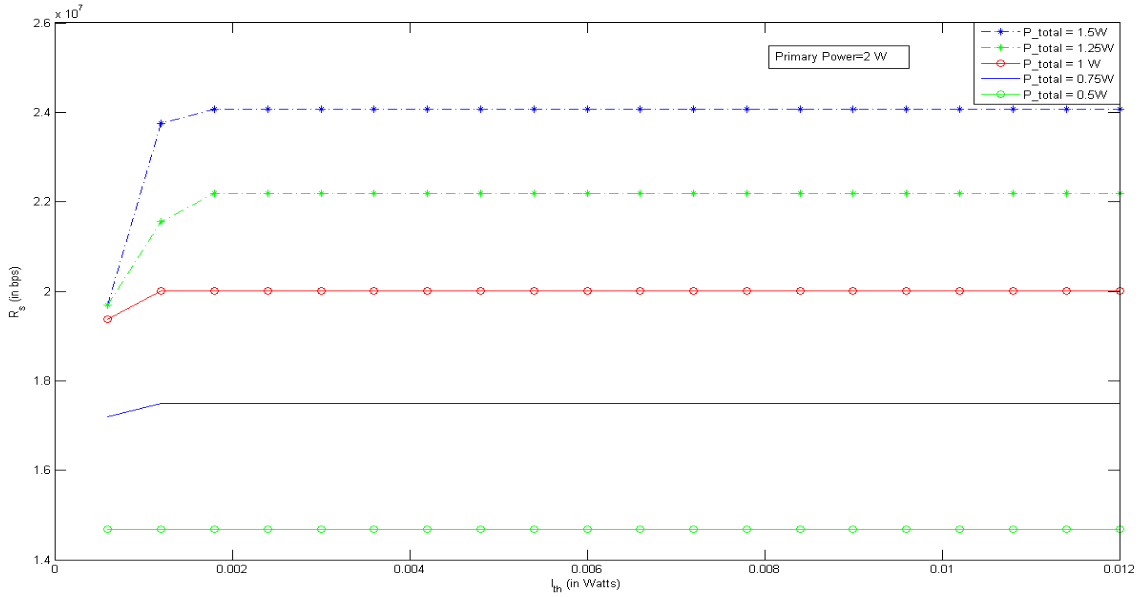


Fig. Plot of Rs v/s I_{th} for different CRU power

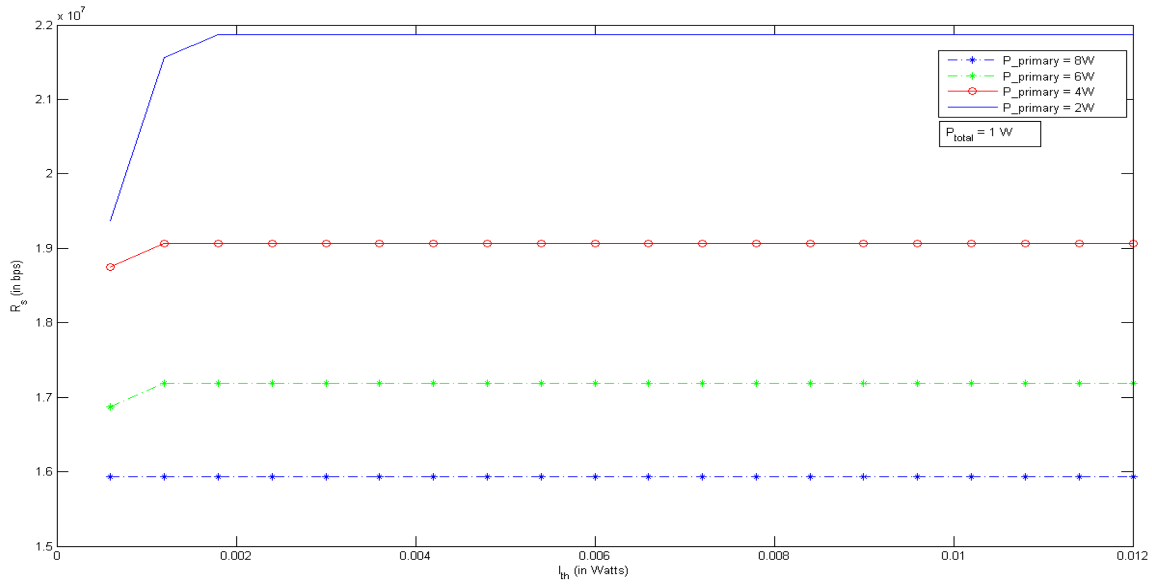


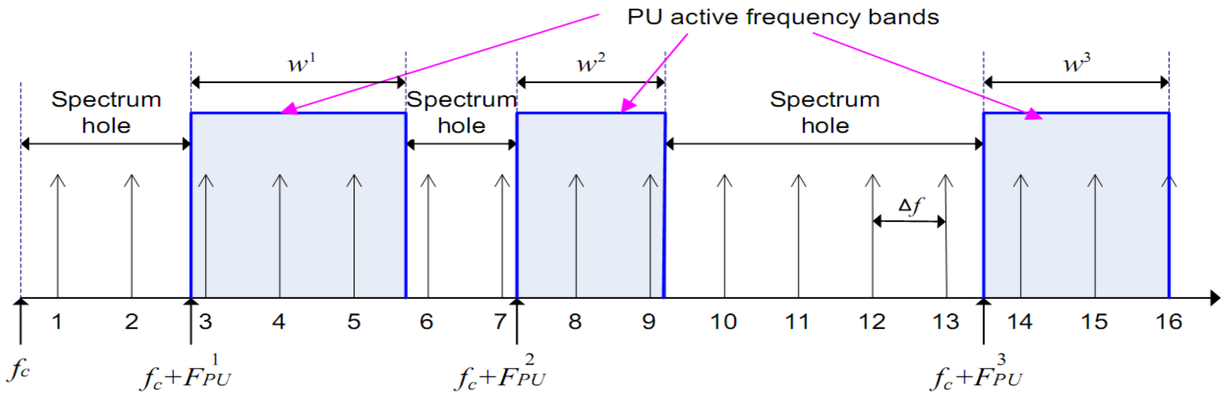
Fig. Plot of Rs v/s It_h for different Primary power

We observed that as I_{th} increases, the total bit rate increases till certain value after which it becomes constant. This is due to the total power constraint provided by the CR system. After the total power limit is reached, the bit rate ceases to increase and thus becomes constant. Total data rate can be increased in levels by increasing the CRU power. Bit rate with no NBRW specified was higher for constant CRU and primary power. As expected, system with low primary power provided way to increase bit rate in levels as I_{th} increased.

3. Max-Min algorithm

The Max-Min algorithm is based on the greedy approach in allocation of radio resources while keeping the constraints in power and interference level. In this, we formulate the optimization as a multidimensional 0-1 knapsack problem and give a low-complexity solution for this. The fairness among users is not bothered because we consider whole CR system as a one user.

3.1. System Model [2]



We have assumed a system containing one CR user and three primary users operating alongside. Since the primary user bands are random in the whole band, the spectrum holes are generated randomly. The total bandwidth of CRU is *W* Hz, and *M* subcarriers are available in the system. The bandwidth of subcarrier *m* ranges from [fc + (m – 1) Δf] to [fc + m Δf]. The time varying gain from CRU transmitter to its receiver for each sub-band *m* is $\sqrt{g_m}$ where g_m is outcome if independent random variable. There is no interference among the subcarriers due to orthogonality. The power gains of sub-channel *m* from CRU transmitter to PU *l*'s receiver and from PU *l*'s transmitter to CRU receiver is denoted by h^l_m and d^l_m respectively. PU *l*'s bandwidth ranges from ($fc + F^l_{PU}$) to ($fc + F^l_{PU} + w^l$).

The interference power generated by PU *l* to the m[th] OFDM sub-channel at the CRU receiver is:

$$f_{PU}^{l,m} = \int_{(m-1)\Delta f-(F_{PU}^{l}+\frac{1}{2}w^{l})}^{(m)\Delta f+(F_{PU}^{l}+\frac{1}{2}w^{l})} d_{m}^{l}\Phi_{PU}^{l}(f)df \qquad (7)$$

where $\Phi_{PU}^{l}(f)$ is the PSD of signal of primary user *l* as in [1].

The number of bits per OFDM symbol, r_m, which can be supported for the CRU on sub-channel *m* is given by:

$$r_m = \left\lfloor \log_2\left(1 + \frac{g_m s_m}{\Gamma(\sigma^2 + I_m)}\right)\right\rfloor \qquad (8)$$

where

s_m is CRU transmission power

σ^2 is noise power

I_m is interference from PU given by:

$$I_m = \sum_{l=1}^{L} f_{PU}^{l,m} \qquad (9)$$

The interference power injected by CRU in subcarrier *m* into the primary band *l* is given by:

$$f_{CR}^{l,m} = \int_{F_{PU}^{l}-(m-\frac{1}{2})\Delta f}^{F_{PU}^{l}-\left(m-\frac{1}{2}\right)\Delta f+w^{l}} h_{m}^{l}\Phi_{CR}^{l}(f)df \qquad (10)$$

where $\Phi_{CR}^{l}(f)$ is the base band PSD of the OFDM signal in sub-band *m* when $s_m = 1$ [1].

The objective is to maximize the overall rate of transmission subject to the specific thresholds. The problem can be formulated as:

$$W = max\sum_{m=1}^{M}\sum_{n=1}^{N} x_{m}^{n}$$

subject to,

$\sum_{m=1}^{M}\sum_{n=1}^{N} p_m^n x_m^n \le S$

$\sum_{m=1}^{M}\sum_{n=1}^{N} p_m^n f_{CR}^{l,m} x_m^n \le I_{th}^l$

$x^n_m \in \{0,1\}$

where,

N is the maximum number of bits that can be allocated on any sub-channel and can be set by the system to any value not exceeding $\log_2\left(1+\frac{SG}{\Gamma}\right)$ with $G = \max(g_m/\sigma^2)$.

$p_m^n \triangleq 2^{n-1}\,\Gamma\,(\sigma^2 + I_m)/g_m$ is the incremental power required to add the n^{th} bit to sub-channel *m* and x^n_m indicates that n^{th} bit of sub-channel *m* is allocated. The efficiency capacity for sub-channel *m* for constraint *l* is given by:

$$c_m(l) = \begin{cases} \frac{S-u_0}{p_m^{\hat{r}_m+1}} & ,l=0 \\ \frac{I_{th}^l - u_l}{p_m^{\hat{r}_m+1} h_m^l f_{CR}^{l,m}} & ,l=1,2,\ldots,L. \end{cases} \quad (11)$$

The terms u_0 and u_l are the costs of resources already allocated, i.e.

$$u_0 = \sum_{m=1}^{M}\sum_{n=1}^{\hat{r}_m} p_m^n \quad (12)$$

$$u_l = \sum_{m=1}^{M}\sum_{n=1}^{\hat{r}_m} p_m^n\ f_{CR}^{l,m} \quad (13)$$

We then greedily allocate a bit to the sub-channel with the largest efficiency value. This process of allocating one bit at a time is repeated until one of the constraints can no longer hold.

3.2. Algorithm [2]

Initialize $\hat{r}_m = 0, \forall m$; $u_l = 0, \forall l$

while $S - u_0 > 0$ and $I^l_{th} - u_l > 0$, l = 1,2,…..,L

  for m = 1 to M

    calculate $c_m(l), \forall l$ using (11)

    $e_m = \min_l \{c_m(l)\}$

  endfor

  $\alpha = \arg\max_m (e_m)$

  $\hat{r}_\alpha = \hat{r}_\alpha + 1$

  update $u_l, \forall l$ using (12) and (13)

endwhile

The Min-Max algorithm has complexity O(RLM) where R is the total number of allocated bits.

3.3. Simulation and result

3.3.1. Parameters used

- All the channel power gains are assumed to be Rayleigh.
- Center frequency (fc) = 20MHz
- Symbol duration = 4us.
- Total bandwidth of the CRU system (W) = 4MHz.
- Number of subcarriers = 13
- Number of CR users = 1
- Number of primary bands = 3
- Noise power (σ^2) = 10^{-8} W.

3.3.2. Graphs for throughput of CR system

For comparison, performance of minimum power algorithm was also plotted.

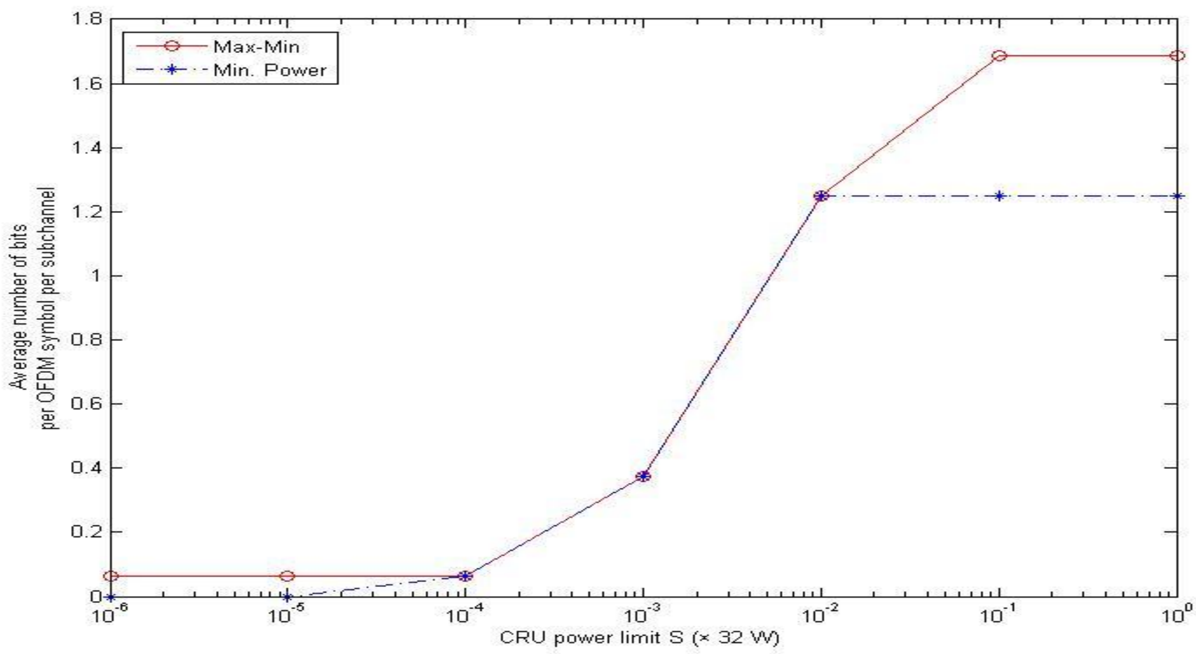


Fig. Graph for average no. of bits v/s CRU power

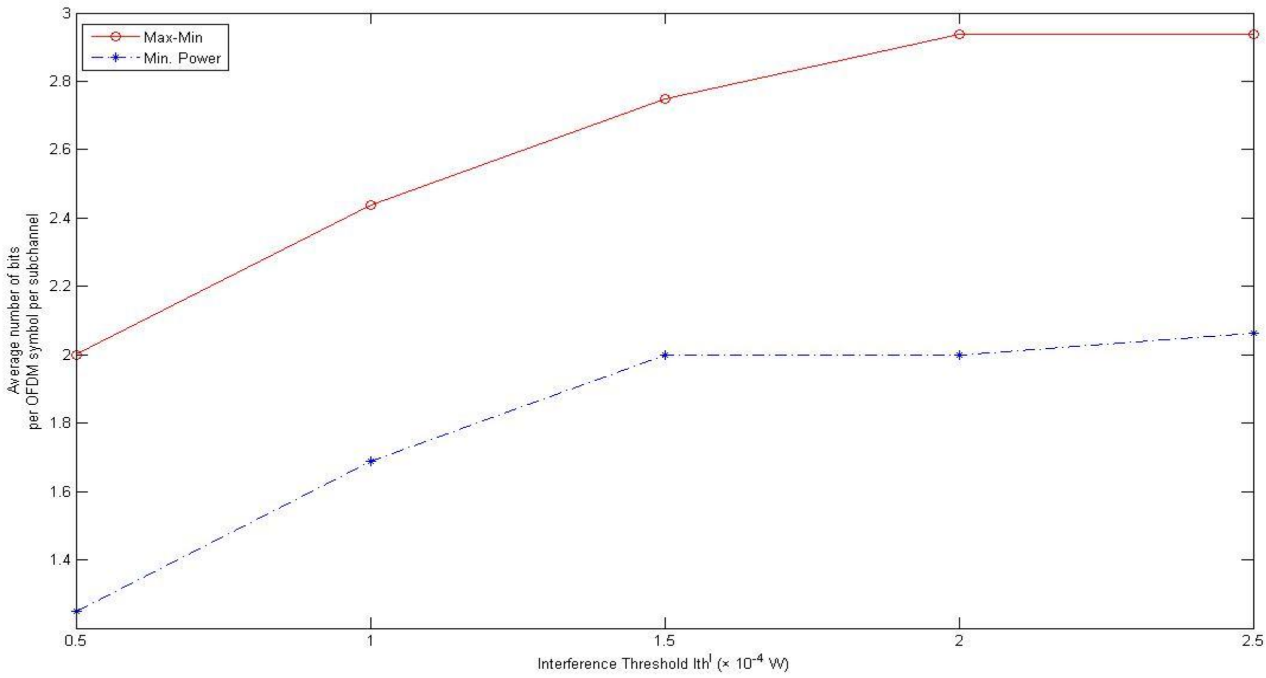


Fig. Graph of average no. of bits v/s I_{th} for each PU

In the first graph the average data rate is plotted versus the total power budget of CR system keeping the interference threshold constant. The average data rate increased with the increasing CRU power till the power constraint is maintained, after which it ceased to increase and became constant. The upper limit of the total power is kept in the sense that the power of CR system above that will cause signal spill to the primary band and thus results in interference, causing the data rate to become constant. In the second graph, the average data rate is plotted versus the interference threshold for constant power of CR system. We found that the data rate increases on increasing threshold because there is still some room for enough interference to occur. The data rate became constant when upper limit in interference threshold was reached because of the total power constraint of the system.

MP algorithm performed poorly against Max-Min algorithm. For every simulation, the MP results were degraded in comparison with the Max-Min algorithm.

4. Particle Swarm Optimization (PSO)

4.1. Introduction

The Particle Swarm Optimization (PSO) is a swarm intelligence-based evolutionary algorithm. It is a biologically inspired algorithm motivated by social analogy. Its aim is to obtain the global optimum of a real-valued function defined in a given space [8]. It was inspired by the behavior of the swarm to look for food. This was introduced first by Kennedy and Eberhart in the year 1995. Kennedy was an American psychologist and Eberhart was an electrical engineer. This algorithm makes use of social behavior and movement dynamics of insects, birds and fish. Let us take example of the fish food searching behavior. The searching space of the fish can be considered as the search space and the fish in the shoal can be considered as small particles denoting solutions in the search space. The process of searching the food can be viewed as an optimization process. In the process, the members of the shoal compete among themselves and share the information with the partners to find the best solution of the problem altogether.

The research have shown that when birds or fishes search for food, they do it in groups (flocks or swarms) and not individually. The observation is based on the assumption that the information is shared inside the group among the individuals. The behavior of each individual is influenced by the behavior of the whole group. The PSO was developed through simulation of the simplified social system and has been found robust in solving non-linear optimization problems [7]. The PSO algorithm can produce simplified and good solution with lesser calculations, shorter time and stable convergence than any other conventional methods.

The PSO is closely related to the Artificial Life and Evolutionary Algorithms. It uses a position-velocity model in a swarm based searching process. A swarm consists of a set of individuals or particles, each representing a potential ‘solution’ of the problem being formulated. Each particle is characterized by its position and velocity in the searching space. The position and velocity determine the searching region. The fitness value for each particle is evaluated by using the position and velocity to determine the solution performance using the avail or the fitness function.

There are various pros and cons of the PSO algorithm which makes it limited in use in certain areas only. It has very efficient global search algorithm and is easy to implement with less number of parameters to be determined. However, it has slow convergence in the refined search stage or has weak local search ability. But still it is simple to use and is immune to the changing the scale of the parameters.

The PSO algorithm is best suited to the continuous variable problems. It has been applied to a number of applications including the Artificial Neural Networks. It is used in the training of Neural Networks in areas like image processing and Fuzzy logic. It can be applied in electrical distribution field for optimized power supply. Various other applications include system identification in biomechanics and biochemistry and in structural optimization of shape and size design.

Two basic types of PSO can be identified based on the processing of the algorithm, synchronous and asynchronous PSO. In synchronous PSO the particles are evaluated parallel first and then they are compared. Generally, a synchronous point is required for all the particles from where again the process can start for iteration. In asynchronous PSO, each particle is evaluated separately and then compared in every step. If a particle is already found to be fit, it need not be re-evaluated, thus saving the computation time.

4.2. Parameters of PSO [7]

1. **Initial Population**: The population is the set of n particles, and is generated randomly.
2. **Population Size**: It refers to the number of particles in a swarm and should be set according to the problem (based on the tradeoff between accuracy and computation time).
3. **Swarm**: It is a set or group of the particles or population which move in random directions.
4. **Search Space**: It is the range in which the algorithm computes the solution. It is the set of solutions defined in a space.
5. **Number of Iterations**: It refers to the maximum number of steps required for the fitness value to converge to an optimal solution.
6. **Inertia weight**: The inertia weight controls the convergence of the algorithm and should be chosen very carefully. Too high or too low inertia weight can lead convergence to fail and no solution will be obtained.

4.3. The Algorithm

The position and velocity of the particles are randomly initialized based on the searching technique. The position of a particle *i* is denoted as $x_{i,k}$ and its velocity by $v_{i,k}$, k being the iteration number. So, the position and velocity can be denoted in vector form by $Xi=[x_{i,1}, x_{i,2}, x_{i,3}.....x_{i,k}]$ and $Vi=[v_{i,1}, v_{i,2}, v_{i,3}.......v_{i,k}]$. An avail function (fitness function) is evaluated for a particle at each iteration using the position and velocity to find out the best solutions. The solution for each particle is then stored in P_{best}. This is known as best local solution and is the best solution it has achieved so far in the iteration. The fitness value is also stored. After all iteration, the best solution for whole swarm is found out as G_{best}.

The position and velocity is updated as the following equations:

$$x_{i,k+1} = x_{i,k} + v_{i,k+1} \tag{14}$$

$$v_{i,k+1} = \omega v_{i,k} + c_1 r_1 (P_{best} - x_{i,k}) + c_2 r_2 (G_{best} - x_{i,k}) \tag{15}$$

where,

ω is the inertia weight

c_1, c_2 are positive accelerators

r_1, r_2 are random numbers

Parameters c_1 and c_2 are constant values. Low values allow the particles to roam far from the target values, whereas the high values result in abrupt movements towards the target values. Normally, their values are set to be 2. The random values of r_1 and r_2 are uniformly distributed between zero and one, [0, 1]. To restrict the searching space, the maximum and minimum values of the velocity and position are defined as [V_{max}, V_{min}] and

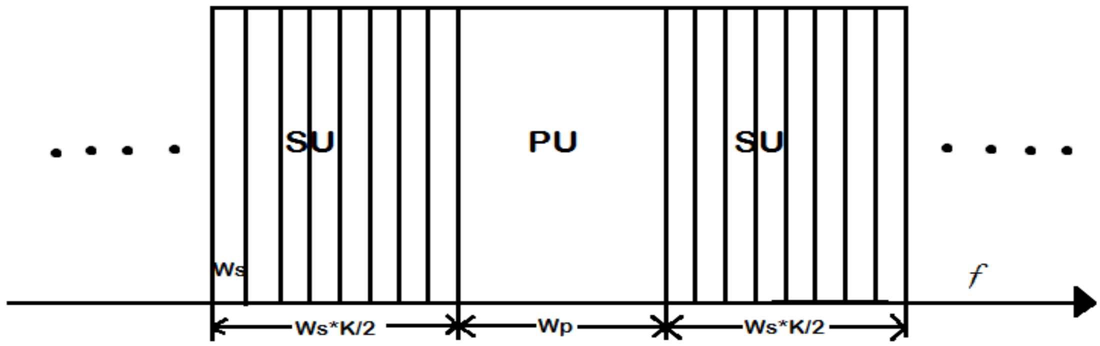
[X_{max} and X_{min}]. The above equations enable the particles to evaluate themselves and update the position and velocity every time to find the optimum for the swarm.

The following steps are involved in the PSO operation:

1. **Initialization**: The position and velocity of the particles are randomly initialized.
2. **Evaluation**: The particles are evaluated by calculating their respective avail function. The current position and the avail values are stored in the P_{best} of each particle. The best position of whole swarm is stored in G_{best}.
3. **Updation**: The position and velocity of particles are updated according to the equations (14) and (15). The particles are again evaluated by their avail values. If the avail value of the updated particle is greater than the current particle, the P_{best} value is replaced by the updated position. Then, G_{best} is updated after all the iteration.
4. **Termination**: When the maximum number of iterations is over or when the stopping criteria are met, G_{best} is the optimal solution. Or else, go to step 3.

4.4. System Model [4]

We have considered two different system models for the simulation of PSO algorithm in resource allocation for cognitive radio systems based on the Channel State Information (CSI) of the system. The first one is for the system having perfect CSI and the second one having imperfect CSI.



4.4.1. System model with perfect CSI [4]

Our system consists of the primary users and secondary users operating side by side in adjacent frequency bands. The secondary users are operating at both side bands of the primary user band while it is active. This can lead to interference among the edge frequencies between primary and secondary users. Let us consider the bandwidth of primary band as *Wp* Hz. We assume that there is *M* numbers of secondary users (cognitive radio users) which are operating on *K* subcarriers, each of bandwidth *Ws*, such that *K/2* subcarriers are active on both sides of the primary band as shown in the figure. So, the total bandwidth of the CR system is *Ws*K/2* Hz. The channels are modeled as slowly time-varying and independently Rayleigh fading. The CSI is known at the transmitter.

The power spectral density of the kth subcarrier is assumed to be:

$$\Phi_k(f) = P_k T_s \left(\frac{\sin \pi f T_s}{\pi f T_s}\right)^2 \qquad (16)$$

where,

P_k is the transmit power of k^{th} subcarrier

T_s is the symbol duration

Let I_k be the interference power introduced by the secondary signal into the primary band.

So,

$$I_k(d_k, P_k) = \int_{d_k - \frac{Wp}{2}}^{d_k + \frac{Wp}{2}} |h_k|^2 \Phi_k(f) df = P_k IF_k$$

(17)

where,

h_k is the channel gain for k^{th} subcarrier

d_k is the spectral distance between k^{th} subcarrier and primary band

IF_k is the interference factor for k^{th} subcarrier

Let S_{mk} be the interference power introduced by primary signal into k^{th} secondary band

$$S_{mk}(d_k) = \int_{d_k - Ws/2}^{d_k + Ws/2} |h_{mk}|^2 \Phi_{RR}\left(e^{j\omega}\right) d\omega$$

(18)

where,

h_{mk} is the channel gain for k^{th} subcarrier for m_{th} user

$\Phi_{RR}\left(e^{j\omega}\right)$ is the PSD of primary user's signal

We formulate the constraint that:

$$\sum_{k=1}^{K} I_k(\, d_k, P_k) \leq I_{th}$$

where,

I_{th} is the interference threshold constraint decided by the PU

According to [4] and [5], we can write the expression for the power allocated to each subcarrier *k* as:

$$P_k = \frac{I_{th}}{IF_k K} + \frac{1}{K}\sum_{k=1}^{K}\frac{\sigma^2 + S_k}{|h_k|^2} - \frac{\sigma^2 + S_k}{|h_k|^2}$$

(19)

where,

σ^2 is the noise variance

Now, with the power and bits allocated to the subcarriers, the data rate of a subcarrier can be denoted as:

$$R_k(P_k, h_k) = \ln\left(1 + \frac{|h_k|^2 P_k}{(\sigma^2 + S_k)}\right)$$

(20)

4.4.2. System model with imperfect CSI [11]

The system model for the resource allocation of CR system with imperfect Channel State Information is same as that of with perfect CSI given above. All the equations for PSD, the power level, interference, data rate and bits per symbol remain same. The previous model was based on the assumption that the transmitter had the true estimation of the channel i.e. there was a full information about channel gain at the transmitter. But, however in practical wireless applications, having a true estimate of channel at the transmitter is not possible and some estimate of the channel has to be made out of statistics, which of course deviates from the true estimate of the existing channel. So, there will be degradation in the overall system performance as compared to the system having perfect CSI.

As previous model, we assume that there is *M* numbers of secondary users (cognitive radio users) which are operating on *K* subcarriers, each of bandwidth *Ws*, such that *K/2* subcarriers are active on both sides of the primary band. In this system model, we have assumed that the transmitter has imperfect or partial Channel State Information, and the channel undergoes an independently Rayleigh fading. We implement PSO for the resource allocation based on the system model.

The channel estimation with imperfect information at the transmitter can be formulated as the sum of the true estimation of channel and estimation error. Let h denote the actual channel gain, which can be referred either from the CR base station to the k^{th} subcarrier of m^{th} user or to the primary user. The estimated channel gain is given by:

$$\hat{h} = h + e \qquad (21)$$

where,

e is the channel estimation error

For simplicity and simulation reasons, e is assumed to be an outcome of independent, circularly symmetric Gaussian random variable.

The maximum bit rate for a subcarrier per user, R_{mk}, depends on the channel gain h_{mk}, transmit power P_{mk} and interference levels. But in this case, the transmitter does not know h_{mk}, instead, it has the information about the estimation $\hat{h}_{mk}$. Therefore, the algorithm calculates the estimated version of bit rate, $\hat{R}_{mk}$. Two conditions arise in this case. If $\hat{R}_{mk} < R_{mk}$, then the higher bit rate cannot be achieved, and if $\hat{R}_{mk} > R_{mk}$, then it exceeds the channel capacity and the total bit rate will be zero. So overall, the maximum bit rate of the system, R_s with imperfect channel estimation will always be less than that of system with true channel estimation.

To reduce the overall throughput degradation due to inaccurate channel gain, a back-off factor B_G has been introduced such that $0 \leq B_G \leq 1$. This factor is multiplied to the channel gain in order to stabilize it and thus normalizing the gain so that there is no extreme change in the gain. So we replace the channel gain h_{mk} in all the equations with $B_G * \hat{h}_{mk}$ and all other steps in algorithm are the same.

4.5. Allocation Algorithm

The maximum number of bits per symbol to be loaded on a subcarrier for any user *m* can be written as:

$$b_{mk} = \left\lfloor \log_2 \left(1 + \frac{|h_{mk}|^2 P_{mk}}{(\sigma^2 + S_{mk})} \right) \right\rfloor$$

(22)

where,

P_{mk} is the power allocated to subcarrier *k* of user *m*

$\lfloor . \rfloor$ is the floor function

Now, the main objective of our algorithm is to maximize the total data rate R_s of the secondary users (of the whole CR system) constrained to the maximum level of interference to primary users and maximum allowable transmit power for every subcarrier. The maximum achievable bit rate is given as:

$$\max Rs = Ws \sum_{m=1}^{M} \sum_{k=1}^{K} b_{mk}$$

And the interference constraint is formulated as:

$$\sum_{m=1}^{M} \sum_{k=1}^{K} I_{mk}(d_{mk}, P_{mk}) \leq I_{th}$$

As for PSO, the avail function or the fitness function can be written as:

$$A(R_s, I_{mk}) = R_s - \chi \left(\sum_{m=1}^{M} \sum_{k=1}^{K} I_{mk}(d_{mk}, P_{mk}) - I_{th} \right)$$

(23)

where,

$A(R_s, I_{mk})$ is the avail value achieved by allocating power and bits to users

χ is the coefficient as a tradeoff between data rate and interference to PU

It is considered in the PSO algorithm the importance of the inertia weight ω which is very crucial for convergence of the algorithm. It is used in conjunction with the updation of velocity and thus controls the impact of the previous velocity to the current velocity. A large ω inhibits the searching in local minima and facilitates the searching globally, whereas a small ω facilitates local searching and convergence [9]. So the value of the ω should be chosen accordingly as per the application. Here, a nonlinear method is adopted to change the value of ω dynamically as the avail value changes.

It is given by [10]:

$$\omega = \begin{cases} \omega_{min} + \dfrac{(\omega_{max} - \omega_{min})(A - A_{min})}{A_{avg} - A_{min}} & , A \leq A_{avg} \\ \omega_{max} & , A > A_{avg} \end{cases}$$

(24)

where,

A_{avg} and A_{min} are the average and minimum avail values

ω_{max} and ω_{min} are the extremisms

This dynamic nature of inertia change assures that when the particles are trapped in local minima, the weight is increased and when it is diverging, the weight is decreased.

4.6. Simulation and Results

4.6.1. Parameters used:

System Model:

- Number of users (M) = 4
- Number of subcarriers (K) = 16
- Center frequency (f) = 2 GHz
- Bandwidth of Primary band (Wp) = 5 MHz
- Bandwidth of subcarrier (Ws) = 312.5 KHz
- Symbol rate (Ts) = 4 μs
- Noise power (σ^2) = 10^{-8} W
- Channel is independently Rayleigh fading
- PSD of primary and secondary signal are same
- Back-off factor (B_G) = 0.84

PSO Algorithm:

- Number of particles = 1000
- Number of iterations = 25
- Tradeoff coefficient (χ) = 100
- Positive accelerator 1 (c_1) = 2
- Positive accelerator 2 (c_2) = 2
- Minimum inertial weight (ω_{min}) = 0.4
- Maximum inertial weight (ω_{max}) = 0.9
- Maximum velocity (V_{max}) = 0.2 * ($X_{max} – X_{min}$), X is the position
- Minimum velocity (V_{min}) = -V_{max}
- The algorithm was run for 25 realizations and then results were averaged out

Separate simulations were carried out for system with perfect CSI and system with imperfect CSI. Also, a comparison was carried out between the two and was plotted in the graph. The graph was plotted for maximum data rate of the system (R_s) versus the Interference threshold (I_{th}) of the system as prescribed by the primary user.

4.6.2. Graphs for throughput of CR system

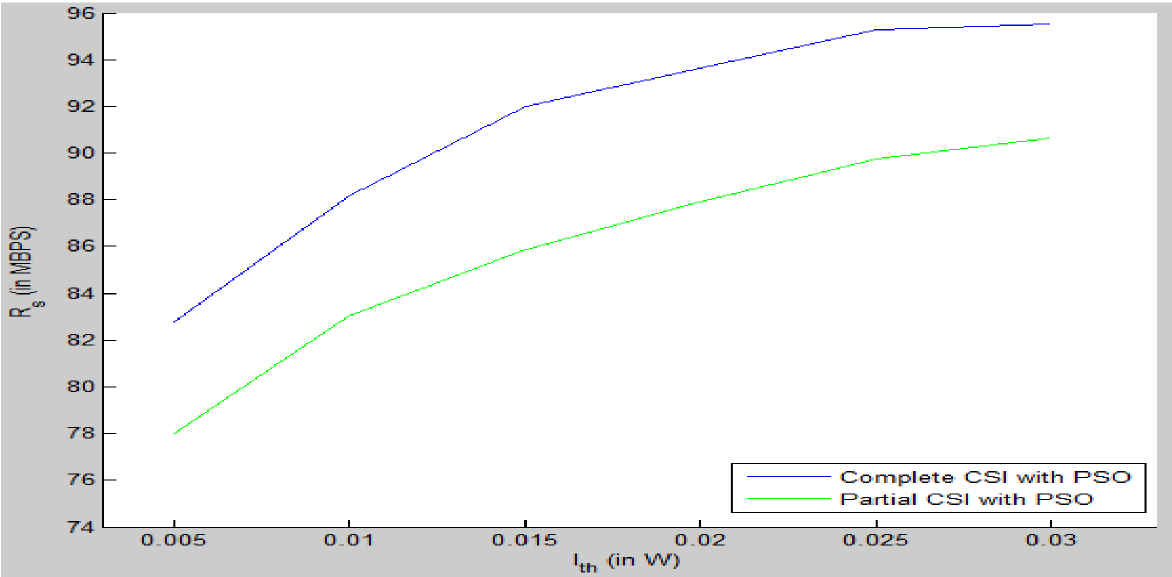


Fig: Plot of data rate versus interference threshold for Perfect and Imperfect CSI using PSO (Primary power = 3 W)

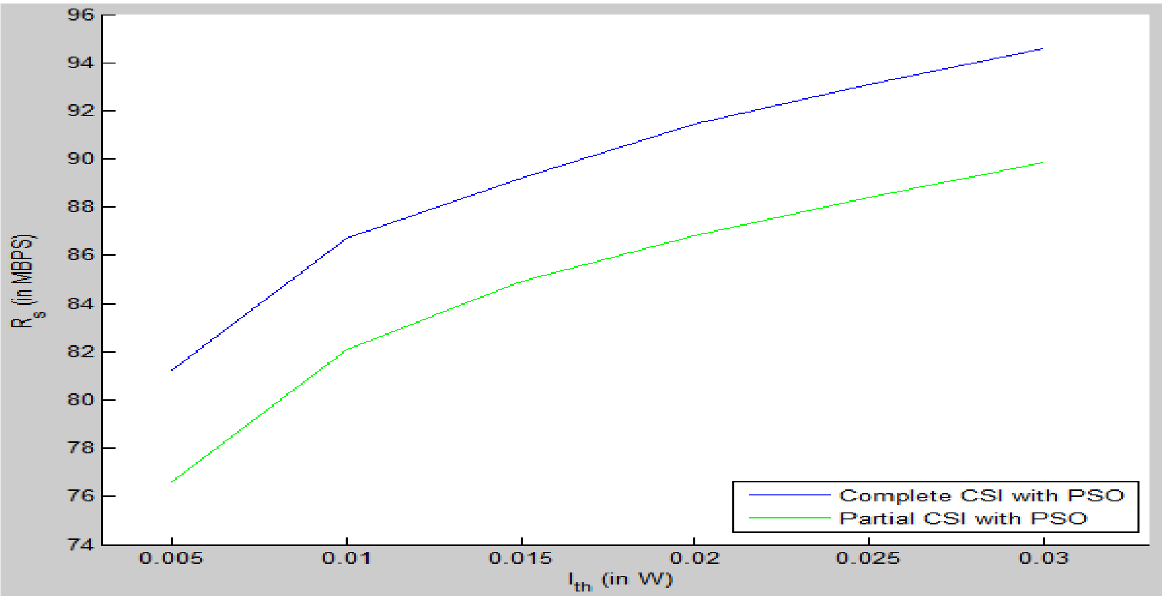


Fig: Plot of data rate versus interference threshold for Perfect and Imperfect CSI using PSO (Primary power = 4 W)

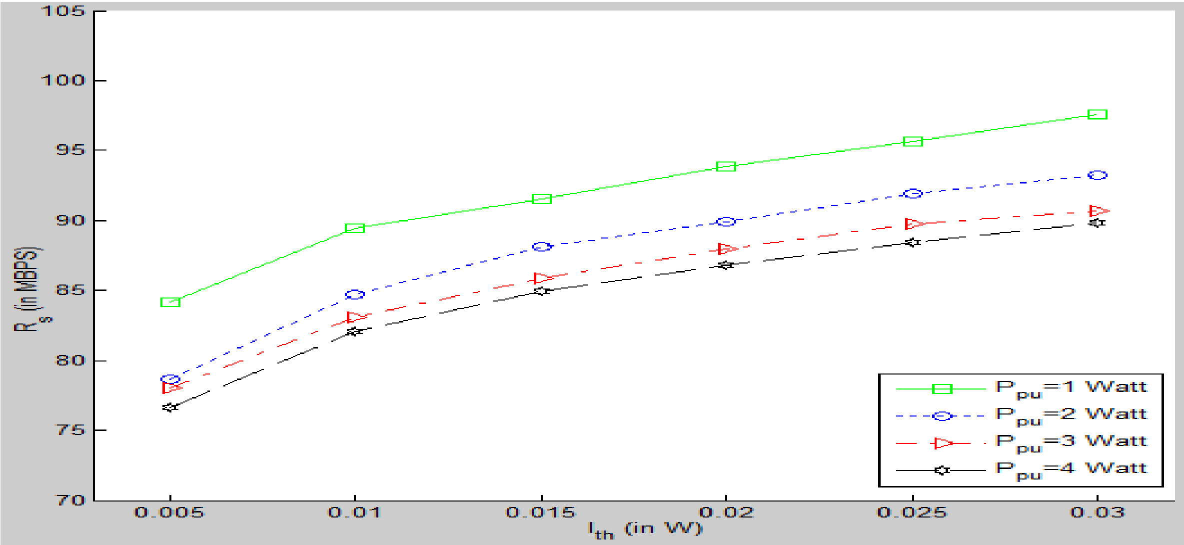


Fig: Plot of data rate versus interference threshold Imperfect CSI using PSO for various P_{pu}

The first graph represents the plot of total data rate (R_s) versus the Interference Threshold (I_{th}) constraint provided by the primary user. The power of the primary user system is assumed to be 3 Watts. We can find out from the graph that the total data rate increases for increasing value of the interference threshold as more and more number of bits can be loaded in the subcarriers with no interference. After reaching the interference limit, the data rate stops increasing and becomes constant.

The second graph represents the plot of total data rate (R_s) versus the Interference Threshold (I_{th}) constraint provided by the primary user. The power of the primary user system is assumed to be 4 Watts. Here also, the total data rate increases for increasing value of the interference threshold till the constrained is reached. By comparing the above two graphs, we find out that the data rate in the system with less primary power is higher than the system with high primary power. This is due to the fact that interference is more easily encountered in system with high power, thus reducing the data rate. The system with imperfect CSI has poorer performance then the system with perfect CSI due to obvious reasons. However, the practical wireless system always has the imperfect CSI to the transmitter, hence is the true performance of the practical system.

5. Genetic Algorithm

5.1. Introduction

Genetic Algorithm (GA) is another biologically (genetically) inspired evolutionary algorithm used to solve complex computational problems to find optimal solutions. It is fully based on biological model of solving problems through various genetic techniques. It uses the principles of selection and evolution to produce several solutions to a given problem [16]. IT is based on the genetic process of many organisms. By mimicking the principle of *natural selection* and process of *survival of the fittest*, as given by *Charles Darwin* in his book, *The Origin of Species*, this algorithm is able to evolve the solutions to the real world problems [18]. This algorithm was first introduced and investigated by John Holland and his students in the year 1975. The GA encodes the potential solution into a specific problem on a simple chromosome- like data structure and applies recombination operators to these structures so as to preserve the critical information.

Like PSO, the Genetic Algorithm also has random population, this time the chromosomes, in the search space which represent the solutions for the problem. The difference being that GA produces new set of population in the solution space as fit individuals. The implementation of Genetic Algorithm begins with the population of random chromosomes. These chromosomes are then evaluated and fittest chromosomes are given reproductive opportunities so as to produce a better set of other chromosomes, which represents better solution. Any set of population are defined better as compared to the current set of population [17].

This algorithm generally thrives in the environment which has a very large set of candidate solutions and in which the search space is uneven and has many hills and valleys. The basic Genetic Algorithm works as described. First, a population (set of chromosomes) is created randomly. Then, each chromosome in the population is evaluated individually based on some fitness function. The fitness function can be anything, as set by the programmer based on the problem and application. Each individual is given a score after the evaluation of how well they have performed. Then, based on the score, two individuals are selected. This selection is completely based on the ranking of the individuals, higher the rank, more the chance of being selected. The selected two individuals are then reproduced to produce one or more offspring. The whole idea is to produce best reproduced individuals from fittest parents. The offspring are then mutated randomly using some method to add to its existing characteristics. This process is continued until the required optimal solution has been found or certain generations have passed. So, the solutions get better and optimal as the generations go by. The GA processes populations of chromosomes, successively replacing one such population with another.

Before performing the GA operation, appropriate coding must be done to the problem. One of the most common forms of coding technique is the binary coding. In this, the chromosome, or the individual of the population is represented using large strands of 0s and 1s. Each value or parameters of a strand is known as *genes*. The most important part while performing GA is the fitness function. The fitness function of an individual returns a single numerical value proportional to the ability of the individual which that chromosome represents.

5.2. The GA Operations

Three types of operators generally are handled in simplest kind of Genetic Algorithm. These are: selection, crossover and mutation.

5.2.1. Selection

As discussed above, the individuals are picked up from the population in order to reproduce. The individuals are selected on the basis of their fitness value. Several techniques are there to select the individuals, out of which the *roulette wheel* selection is the most common. In roulette wheel selection, individuals are given a probability of being selected that is directly proportionate to their fitness value. Two individuals are then chosen randomly based on these probabilities and produce offspring. The fitter the chromosome, the more times it is likely to be selected to reproduce.

5.2.2. Crossover

Crossover is the form of reproduction between two individuals. Generally, a single point crossover is used. In this method two individual chromosomes are taken and a random point is chosen along the strands from where each individual chromosome is cut into two segments. These segments are referred to as *head segments* and *tail* segments. The tail segments are then swapped between two individuals thus producing the two new individuals and are added to the population. Since only one point is chosen in each chromosome to crossover, it is known as single-point crossover. For example, the strings 10000100 and 11111111 could be crossed over to produce the two offspring 10011111 and 11100100. Here, the crossover point is the 4^{th} gene in each strand. The crossover operation roughly mimics biological recombination between two single chromosome organisms. Crossover does not necessarily always occur, however. Sometimes, based on a set probability, no crossover occurs and the parents are copied directly to the new population. The probability of crossover occurring is usually 60% to 70%.

5.2.3. Mutation

After the crossover, the new chromosomes are added to the populations, or not necessarily this happens, in which case the parents are directly copied and kept into the population. So, to ensure the uniqueness of individuals in the population, mutation is performed for certain individuals. In mutation, where binary encoded chromosomes are used, some of the bits in a chromosome are randomly flipped, making them unique in the population. For example, the string 00000100 might be mutated in its second position to yield 01000100. Mutation can occur at each bit position in a string with some probability, usually very small (e.g., 0.001). Mutation is, however, vital to ensuring genetic diversity within the population.

5.3. The Algorithm

A simple Genetic Algorithm works as follows, if given a clearly defined problem to be solved and a bit string representation for candidate solutions.

1. A population of *n*, *l*-bit chromosomes is randomly generated, which are the candidate solutions to the given problem.
2. Each chromosome is evaluated using the fitness function and a fitness value is assigned to each one of them.
3. The following steps are repeated until *n* offspring have been created:

a. A pair of parent chromosomes is selected form the current population with the probability of selection being an increasing function of fitness. That is, the two fittest chromosomes are taken as a pair. The selection is done with replacement, which means that the same chromosome can be selected more than once to become a parent.

b. The pair is then crossed over at some randomly chosen point, chosen with uniform probability. It is done with some probability, which is known as the *crossover probability* or *crossover rate*. If no crossover takes place, two offspring are formed that are exact copies of their parents.

c. The two new offspring are then mutated at some random point with some probability, known as *mutation probability* or *mutation rate*. Then the resulting chromosomes are placed in the new population.

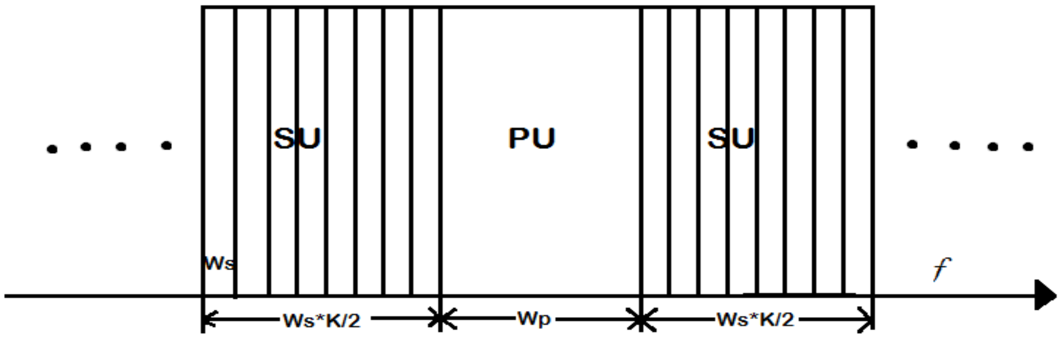
   If n is odd, then one new chromosome can be discarded at random.

4. The current population is replaced with the new population.
5. Go to step 2 and continue until optimal solutions are obtained or desired number of generations is reached.

Each iteration of this process is called a *generation*. A GA is typically iterated for anywhere from 50 to 500 or more generations. The entire set of generations is called a *run*. At the end of a run there are often one or more highly fit chromosomes in the population. Since randomness plays a large role in each run, two runs with different random−number seeds will generally produce different detailed behaviors.

5.4. System Model [4]

The system model used to perform Genetic Algorithm is same as that used for PSO.



Our system consists of the primary users and secondary users operating side by side in adjacent frequency bands. The secondary users are operating at both side bands of the primary user band while it is active. The bandwidth of primary band is *Wp* Hz and that of one secondary subcarrier is *Ws* Hz. *M* users are operating on K subcarriers. So, *Ws*K/2* Hz of subcarriers are operating at each side of the primary band.

In this case also, we have considered the case of system with perfect and imperfect Channel State Information. First the system where the transmitter has the true channel information is considered and simulated. Then the results are compared to the one having imperfect channel information. The equations, power and interference constraints, the data rate equations and the fitness function all are same as considered for the case of PSO. So, we are using two different algorithms for resource allocation in the same CR system, and also comparing the performance of both algorithms.

Like for PSO, the fitness function can be written as:

$$A(R_s, I_{mk}) = R_s - \chi\left(\sum_{m=1}^{M}\sum_{k=1}^{K} I_{mk}(d_{mk}, P_{mk}) - I_{th}\right)$$

where the letters and symbols have their usual meanings. (Refer to section 5.4 and 5.5)

5.5. Simulation and Result

5.5.1. Parameters used:

System Model:

- Number of users (M) = 4
- Number of subcarriers (K) = 16
- Center frequency (f) = 2 GHz
- Bandwidth of Primary band (Wp) = 5 MHz
- Bandwidth of subcarrier (Ws) = 312.5 KHz
- Symbol rate (Ts) = 4 μs
- Noise power (σ^2) = 10^{-8} W
- Channel is independently Rayleigh fading
- Back-off factor (B_G) = 0.84

Genetic Algorithm:

- Number of chromosomes = 20
- Number of generations = 40
- The algorithm was run for 25 realizations and then results were averaged out

5.5.2. Graphs for throughput of CR system

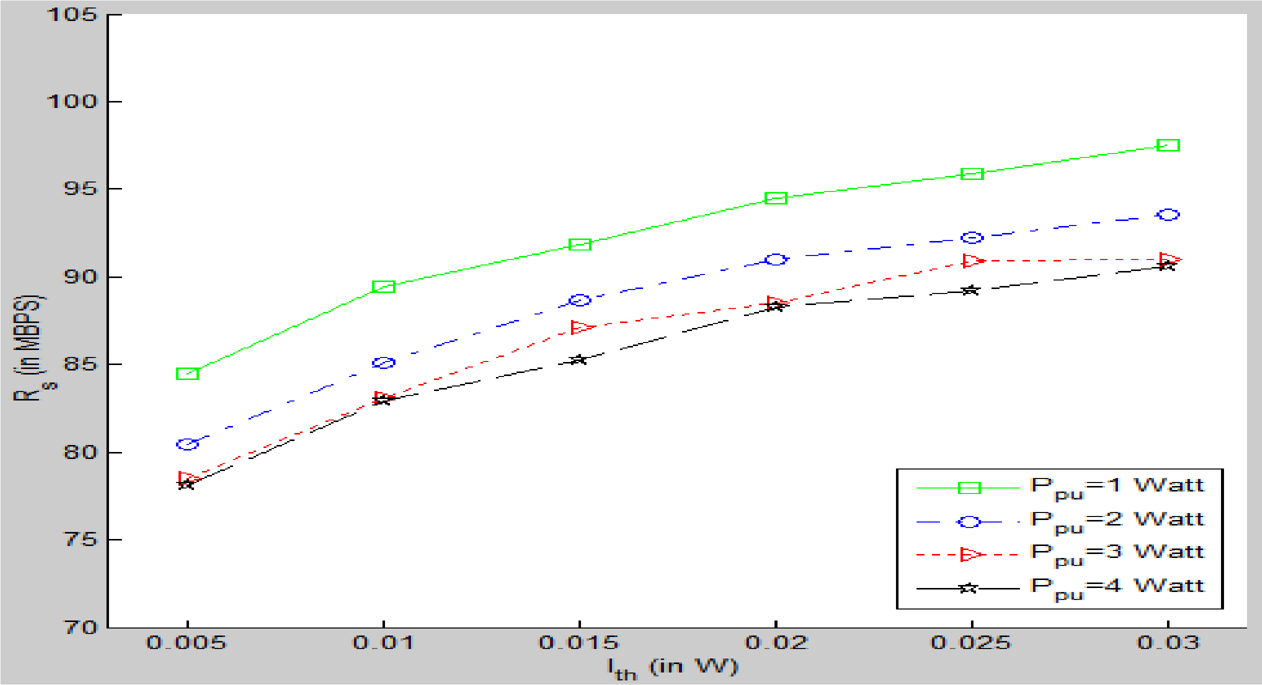


Fig: Plot of data rate versus interference threshold for GA with various primary power

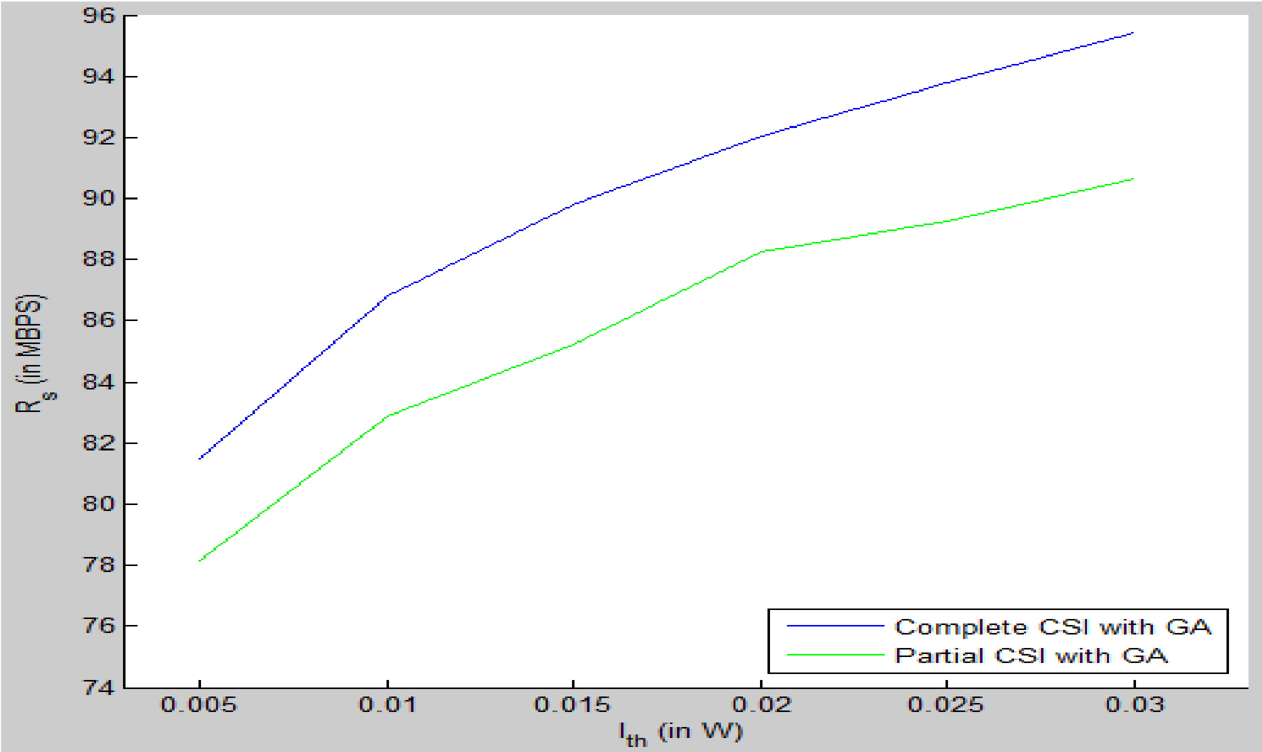


Fig: Plot of data rate versus interference threshold for Perfect and Imperfect CSI GA with primary power = 3W

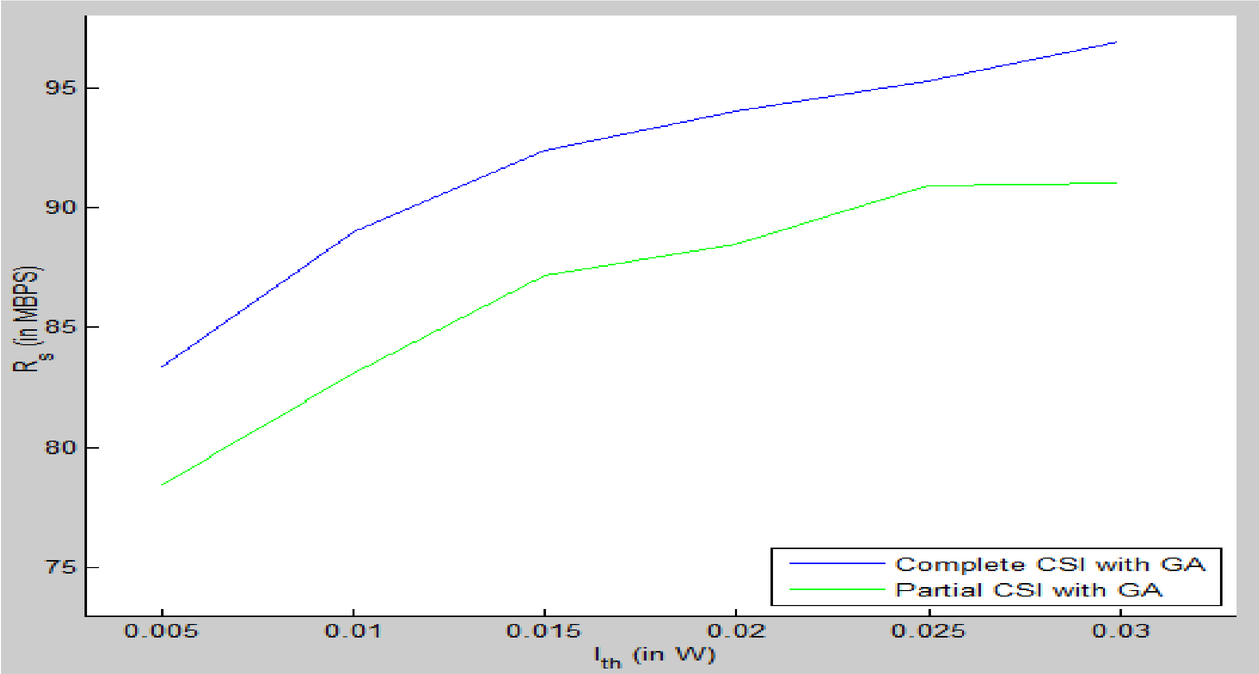


Fig: Plot of data rate versus interference threshold for Perfect and Imperfect CSI using GA (Primary power = 4 W)

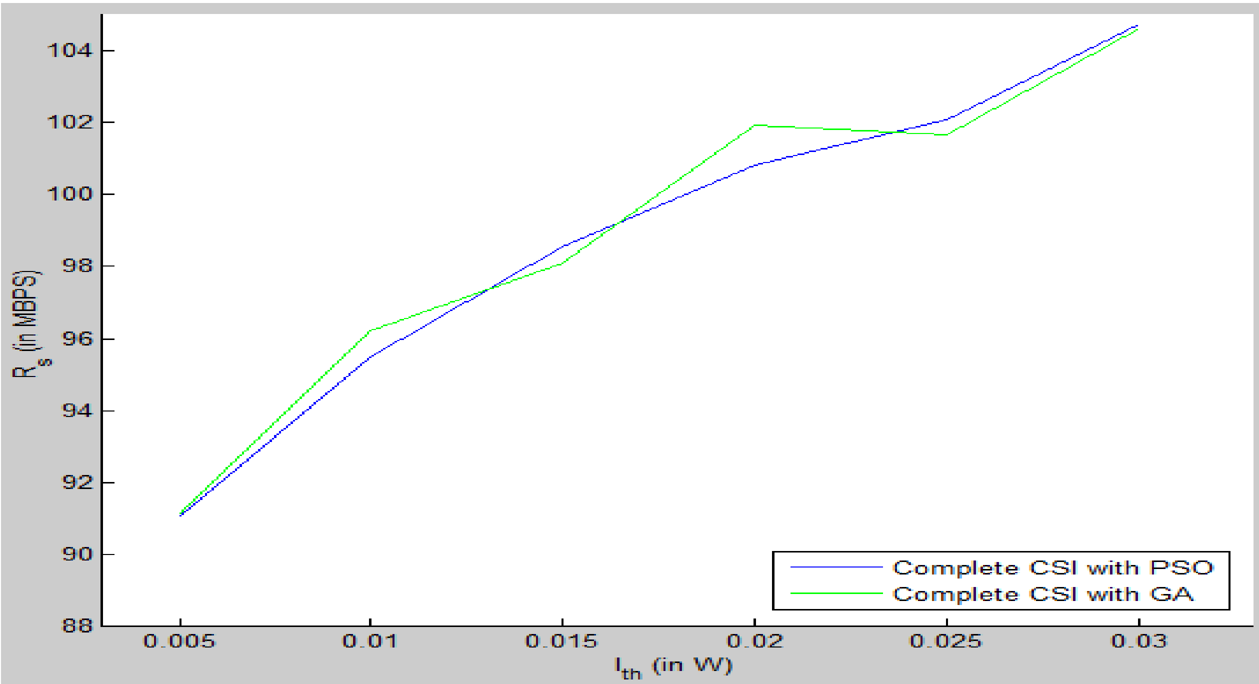


Fig: Plot of data rate versus interference threshold for PSO and GA in perfect CSI (Primary power = 1W)

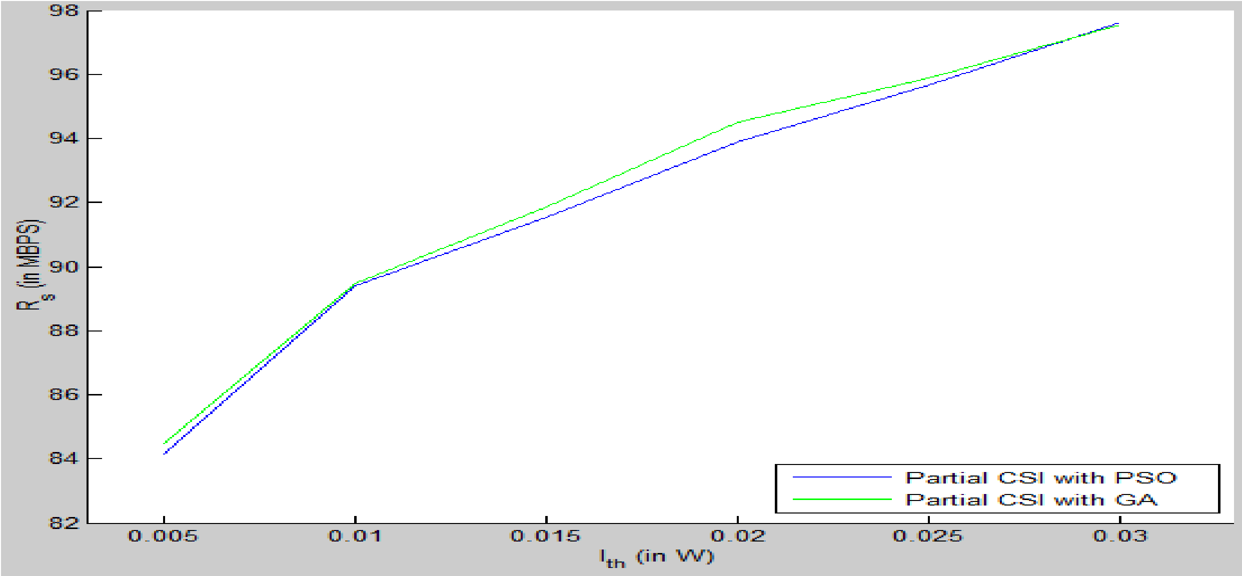


Fig: Plot of data rate versus interference threshold for PSO and GA in imperfect CSI

(Primary power = 1W)

The first graph is the performance of Genetic Algorithm under perfect CSI for various primary power levels. As the power of primary system increases, the data rate decreases in levels as interference increases. This is plotted against increasing interference threshold as provided by the primary system.

The next two graphs are the comparison of performance of Genetic Algorithm for different primary power and under perfect and imperfect CSI. These graphs represent the plot of total data rate (R_s) versus the Interference Threshold (I_{th}) constraint provided by the primary user. The power of the primary user system is assumed to be 3 Watts in first graph and 4 Watts in second graph. We can find out from the graph that the total data rate increases for increasing value of the interference threshold as more and more number of bits can be loaded in the subcarriers with no interference. After reaching the interference limit, the data rate stops increasing and becomes constant. However, the performance of the system with imperfect Channel State Information is inferior as compared to the system with perfect CSI. Again, system with imperfect CSI is practical among the wireless systems. The system with low primary power has higher data rate whereas the system with high primary power has low data rate for interference issues.

The last two graphs are the comparisons between PSO and GA for perfect and imperfect CSI for primary power of 1 Watt. We can see that both algorithms have similar performances as they both produce optimal solutions for the problem. However, GA is inferior to PSO in the sense that more computational time is required for GA and is slow compared to PSO. This is due to many operations required for GA. Therefore, PSO is preferred over GA for similar type of applications.

6. Conclusion

Hence, various sub-optimal and optimal algorithms were studied and implemented for the purpose of dynamically allocating the resources for the Cognitive Radio Systems. Some algorithms were directly implemented from certain papers, which are the work done by esteemed engineers, and simply their behavior was studied. First, a low-complex Fair Adaptive algorithm was implemented from [1]. We used the system model where a primary band was operating side by side to the secondary band in a multi user system. So, interference issues had to be taken care of. Sub-optimal approach was used to simulate the behavior of the throughput of the system as Reduced Complexity (RC) algorithm. It allocates the resources to users in a fair manner, without any power or bits favor to any particular user. The second algorithm we implemented was Max-Min Algorithm [2]. It used the greedy approach to allocate resources to the user. Only one CR user was considered and three primary users were operating side by side. We formulated the optimization as a multidimensional 0-1 knapsack problem and provided a low-complex and sub-optimal solution for this.

Then we studied and implemented Particle Swarm Optimization (PSO), which provides with low-complex optimal solution. Its performance was far better than the previous algorithms. We used the system model of [4] where a primary band is operating side by side to the multi-user CR system. We simulated the PSO for two types of system, one where the transmitter has full information about the channel state and the other where the transmitter has only partial information about the channel. The first case is referred to as system with perfect CSI and the second as imperfect CSI. The system with imperfect CSI is the most practical wireless system where true estimation of channel cannot be done. As expected, the performance of imperfect CSI system was inferior compared to that of having perfect CSI.

Last, we studied and implemented Genetic Algorithm, which, like PSO, provides the most optimal solution for the complex problems. Hence this algorithm can be comparable to the PSO. Again, the same system model was used as [4] and the algorithm was simulated for two types of system, one having perfect CSI and another having imperfect CSI. The performance of the system with this algorithm was comparable to the PSO, the difference being in only the computational time where GA took more time in producing the solutions. This is based on the fact that GA requires more operations to perform than PSO and hence takes longer time.

So, we conclude that Particle Swarm Optimization algorithm is best suited for dynamic resource allocation in Cognitive Radio Systems where the resources are allocated in a dynamic environment within the given constraints of power and interference in a very optimal manner.

7. References

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