# Optimisation of Cognitive Engine Design using Cultural Algorithm

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## Abstract

**Objectives:** To optimize the design of cognitive radio engine using Cultural Algorithm (CA). The simulated results are compared with commonly used Evolutionary Algorithms (EA) like Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA). **Methods/Statistical Analysis:** Use of CA has been proposed to find a suitable fitness score under varying channel conditions over multiple iterations. Matlab has been chosen as the platform for simulating various scenarios. An attempt has also been made to optimize the time of convergence. **Findings:** Simulations indicate that CA emerges as a potential candidate for designing of CR Engine (CRE) for deployment of a CR Network (CRN). Using CA, the fitness score has improved as compared to other EAs. **Improvements:** The algorithm shows faster convergence and improves its performance with each successive iteration.

**Keywords:** Cultural Algorithm, Cognitive Radios, Cognitive Engine, Environmental Parameters, Fitness Functions

## 1. Introduction

With the advent of wireless technologies and miniaturization fast and efficient computing devices, the requirement of radio spectrum has become more stringent. With wideband wireless system technologies like WiMax, Long Term Evolution (LTE), Wi-Fi etc the number of mobile computing devices has been increasing exponentially. Figure 1 indicates that number of mobile phone internet users in India has increased from 237 million in 2014 to 323 million by 2016, and is expected to reach 525 million by 2021. India and China are the only two countries in the world which have a population of over billion people. While the number of mobile phone users in China crossed one billion in 2012, India's mobile phone users crested past the one billion mark in the early 2016. The statistics reveals that the EM spectrum is continually becoming more and more populated, and endeavor should be made to optimally utilize the existing spectrum using cognitive radio technology. The comparison of Mobile phone internet penetration in India with global penetration is shown is Figure 2.
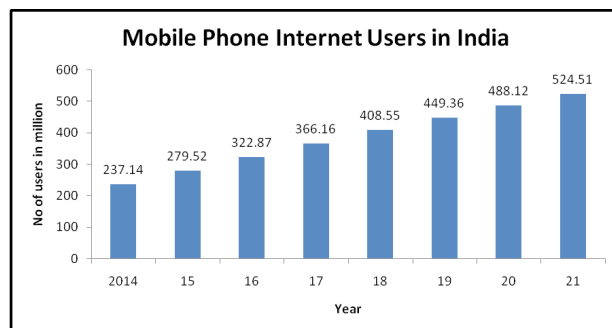


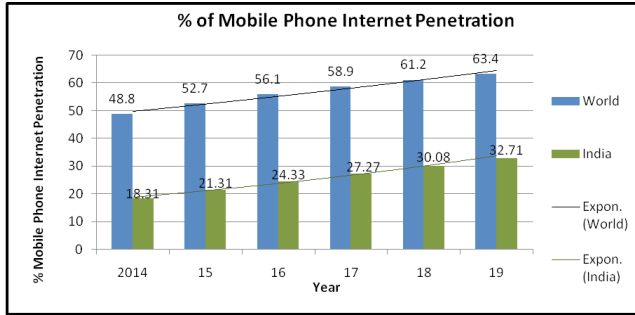**Figure 1.** Mobile phone internet users in India.

**Figure 2.** Comparison of mobile phone internet penetration in India with global penetration.

Most of the study in CR is confined to spectrum sensing. However, allocation of this spectrum is also a critical aspect which needs to be carried out efficiently. Apart from cognitively adapting to the available frequency spectrum, a CR can also adapt to various channel conditions and Quality of Service (QoS) that may hinder effective communication for the available bandwidth[3–7]. In order to achieve this functionality, the transmit parameters are varied cognitively in accordance with existing environmental conditions. In this paper we introduce design of Cognitive Engine using CA and further compare its performance with commonly used EAs like PSO and GA under different operating conditions.

## 2. Artificial Intelligence and Cognitive Engine Design Parameters

The inputs to a cognitive engine are in terms of performance objectives which are derived through the information gathered by it from the surrounding environment in terms of environmental parameters. Some of the environmental parameters which directly affect the operational state of wireless communication are summarized in Table 1[8].

**Table 1.** Environmental parameters

| Ser No | Parameter | Description |
|---|---|---|
| 1 | Signal Power | Signal power as seen by the receiver |
| 2 | Noise Power | Noise power density for a given channel |

| 3 | Delay Spread | Variance of the path delays and their amplitudes for a channel |
|---|---|---|
| 4 | Battery Life | Estimated energy left in the batteries |
| 5 | Power Consumption | Power consumption of the current configuration |
| 6 | Spectrum Information | Spectrum occupancy information |

CR is best implemented using Software Defined Radios (SDR). SDR provides certain control parameters which together with environmental parameters act as an input to the cognitive engine. An exhaustive list of transmission parameters needs to be defined so as to enable the cognitive engine employ a variety of techniques over a wide spectrum of communication systems. Some of the commonly employed transmission parameters have been summarised in Table 2[8].

**Table 2.** Transmission parameters

| Ser No | Parameter | Description |
|---|---|---|
| 1 | Transmit Power | Raw transmission power |
| 2 | Modulation Type | Type of modulation |
| 3 | Modulation Index | Number of symbols in a given modulation constellation |
| 4 | Carrier Frequency | Centre frequency of the transmission signal |
| 5 | Bandwidth | Bandwidth of transmit signal |
| 6 | Channel Coding Rate | Specific rate of coding |
| 7 | Frame Size | Size of transmission frame |
| 8 | Time Division Duplexing | Percentage of transmit time |
| 9 | Symbol Rate | Number of symbols per second |

Wireless channel conditions are highly dynamic in nature, thus a CR has to continuously endeavour upon improving the link state to maintain the desired quality

of communication. In order to realize this aspect, certain performance objectives that merit attention of a CR are Bit Error Rate (BER), throughput, power consumption, interference and spectral efficiency. Depending upon the prevailing channel conditions, a CR aims at minimising the overall BER so that the effective throughput achieved over the link can be maximized. Similarly, channel conditions will also dictate the reach of the link and accordingly the transmission power can be controlled or varied. There may be instances wherein a link may be engineered over fairly large distances with appreciable throughput with medium/low transmission power. However, when the channel is noisy and the BER is high, the radio may have to be operated on a high power mode so as to maintain the desired link quality. All these parameters and objectives are learnt by the Cognitive Engine from the operating environment through cognition which is infused into the system by various artificial intelligence algorithms which are discussed in the next section.

# 3. Metaheuristics In Cognitive Radio Engine Design

One of the major challenges in implementation of CR is large search space. Heuristics and Metaheuristic techniques provide answers to the challenges of large search spaces. While heuristics approach focuses on approximate optimization technique as they do not search over the complete sample space, metaheuristic approach are more generalized optimisation algorithm and can be applied to much wider range of problems rather than specific optimisation requirements. This aspect makes metaheuristics a much favoured approach for CRN. The beauty of metaheuristics lies in the fact that its implementation can be customized to solve a particular problem.

Metaheuristics achieve cognition through three broad modes supervised learning, unsupervised learning and reinforcement learning. Either of these modes can be employed either individually or as a combination in a CRN. In this section we will briefly discuss some of the most commonly employed evolution algorithms.

## 3.1 Particle Swarm Optimisation (PSO)

This algorithm falls under the category of Swarm Intelligence (SI) which is a tributary of Artificial Intelligence (AI). It is based on the behavioural patterns displayed by flock of birds or swarm of fishes. It utilises the property of homogeneity, locality, velocity matching and flock centring for the purpose of finding an optimum solution.

In PSO, a swarm can be defined as a structured collection of interacting agents. The knowledge about experimental environment is refined through iterative interaction between every individual entity thereby steadily progressing towards an optimal solution. In this algorithm, we define a set of particles of swarm, where each individual particle represents a potential solution over the entire sample space characterised by position and velocity. With each iteration, every particle updates its position and velocity based on its own best position as well as the global best position of the entire swarm. The particle update rule can be summarised as under:

$$p = p + v \tag{1}$$

$$v = v + c_1 \times rand \times (p_{Best} - p) + c_2 \times (g_{Best} - p) \tag{2}$$

Where $p$ is the particle's position, $v$ is the path direction, $c_1$ is the weight of local information, $c_2$ is the weight of global information, $p_{Best}$ is the best position of the particle, $g_{Best}$ is the best position of the swarm and rand is a random variable. PSO finds its usage in solving CR problem is by the virtue of its simplistic algorithmic steps, complexity and fast convergence time[9–12].

## 3.2 Genetic Algorithm

In Genetic Algorithm (GA), candidate solutions known as individuals, creatures or phenotype form a population of solutions to an optimisation problem. Each candidate solution evolves genetically towards a better solution. Every candidate solution or phenotype has a set of properties called chromosomes or genotypes associated with it. These chromosomes can be mutated or altered as desired to a new population. These chromosomes interact randomly in an iterative manner. The entire population that participates in a particular iteration is called a generation. Whether a candidate solution fits in a particular generation, depends upon a fitness parameter defined by a fitness function. Chromosomes with better fitness values are selected from the current population and each individual chromosome is suitably mutated to form a new generation of solutions. Thus with a change in generation fitter candidates and their off-springs are allowed to evolve to the next generation whereas the weaker solutions are filtered out. Thus with each generation a much

refined and better solution to an optimisation problem is achieved. Another concept that is widely employed is that of Crossover in which fragments of two chromosomes are combined to create two new chromosomes which are other solutions in the desired sample space. While crossover combines two chromosomes to form two new chromosomes, Mutation changes a gene randomly with the hope of reaching better solutions[13]. The algorithm terminates when the maximum number of iterations have reached or desired fitness level is achieved by the participating population. In[14] authors have considered radio identity and modulation type which are both coded into binary chromosomes. Each chromosome has N blocks and each block consists of two parts; first part identifies the radio pair assigned to a subcarrier and is represent by $log_2$K bits while the second part uses two bits to represent the modulation type used. The length of each chromosome is given by $N \times (log_2 K + log_2 Q)$ where $log_2$K represents the number of bits to uniquely identify the users and $log_2$ Q represents number of bits required to represent modulation level.

## 3.3  Cultural Algorithm

The theory of evolutionary computation revolves mostly around use of concepts, principles and other mechanisms derived from the evolution of natural systems for solving complex computational problems. Reynolds states that "Cultural evolution enables societies to evolve or adapt to the environment at rates that exceeds that of biological evolution based upon genetic inheritance alone". Culture has been defined as system of symbolically encoded conceptual phenomenon that is socially and historically transmitted within and between populations[15].

Complex computations have been possible using EA owing to their unbiased approach despite being unaware of the domain knowledge. If somehow the approach of these algorithms is biased to solve the problem statement, so as to identify patterns in their performance environment, then these patterns can then be suitably utilized to promote instances of desirable candidates or weaning out weaker or undesired candidates in the population. Culture is a ubiquitous repository of information, freely accessible to the entire population which helps promoting constructive interaction of various individuals in the entire population base. This process facilitates the self-adaptive knowledge and stores this information to direct evolution of the social population.

Thus both knowledge and beliefs are inherited by the next generation from the current generation and this is the reason why cultural systems are said to be possessing dual inheritance. The knowledge and beliefs acquired from the previous generations help the present generation to seek better solutions and thus acquire a better fitness score from their ancestors.

In CA, each candidate solution is evaluated on basis of a fitness factor. This fitness factor may give a measure of problem solving capability or experience of the individual. Those amongst the current population, who respond positively, impact or contribute to the current belief, are known to respond to an acceptance function. An acceptance function determines which individual in the current population are able to impact or to be voted to contribute to the current belief. This knowledge is stored and manipulated in the belief space and this process is known as adjusting the belief space. The experience of these selected candidates is used to further improve the current belief. This improved group belief then helps in guiding and influencing the evolution of the population in the present generation to the next generation. The knowledge and the acquired belief of the population level interact with each other through a communication protocol which identifies suitable candidates who are able to update the belief space and also determines how the updated beliefs help in influencing and impacting the population component[16–18]. CA can be used using any of the following modes of operation which given in the subsequent paragraphs.

### 3.3.1  Understanding Belief Space

The belief space is a central natural repository of information or knowledge where the collective behaviour or beliefs of individuals in population space is stored. It is sometimes also referred to as meme pool, where meme is a generalized experience of individuals within the population space which acts as a unit of information transmitted through behavioural means[15]. The information or knowledge is accumulated over a multiple generations in the belief space. As the search is biased through the domain knowledge or the knowledge inherited from the previous generations, it results in significant pruning of the population space. The knowledge residing within the belief space filters the optimal solutions, resulting in better solutions with each generation[19,20].

The knowledge base existing within the belief space is categorised based on the domain which it represents. Accordingly, the belief has been classified into five basic categories[21]:

- **Normative Knowledge:** This is a set of desirable value ranges which are expected to reside within the population space. e.g. acceptable behaviour for the agents in the population.
- **Domain Specific Knowledge:** Called prior in the Bayesian statistics, it reflects some knowledge pertaining to the problem being optimized.
- **Situational Knowledge:** This domain refers to the knowledge pertaining to the vital incidents in the search space. e.g. successful/ unsuccessful solutions.
- **Historical/Temporal Knowledge:** The knowledge residing in the history of the search space. e.g. temporal patterns of the search space, is factored here.
- **Spatial Knowledge:** The information on the landscape or topography of the search space is factored under this head.

In this paper we have considered only two components viz. situational and normative knowledge, and represented the belief space as a tuple

$$\mathcal{B}(t) = \big(\mathcal{S}(t), \mathcal{N}(t)\big) \tag{3}$$

here $\mathcal{S}(t)$ represents the situational knowledge component whereas $\mathcal{N}(t)$ represents the normative knowledge component in the belief space. The set of best solutions is encapsulated within the situational component and normative component as under

$$\mathcal{S}(t) = \{\widehat{\beta}_l(t) : l = 1, 2, \ldots \ldots \ldots n_s\} \tag{4}$$

$$\mathcal{N}(t) = \Big\{\chi_1(t), \chi_2(t), \ldots \ldots \chi_{n_x}(t)\Big\} \tag{5}$$

for each dimension in equation (5) following information is stored

$$\chi_j(t) = \big(\mathbb{I}_j(t), \mathbb{L}_j(t), \mathbb{U}_j(t)\big) \tag{6}$$

where $\mathbb{I}_j$ denotes a closed interval,

$$\mathbb{I}_j(t) = [\alpha_{min,j}(t), \alpha_{max,j}(t)] = \{\alpha : \alpha_{min,j} \leq \alpha \leq \alpha_{max,j}\} \tag{7}$$

and $\mathbb{L}_j, \mathbb{U}_j$ represents the lower and the upper bounds respectively.

### 3.3.2 Acceptance Function

Acceptance function selects those individuals from the population space who help shaping the belief space in a favourable manner. A variety of selection techniques may be employed e.g. elitism, tournament selection or roulette-wheel selection, given that the number of individuals remains the same. The number of individuals is determined as

$$\eta_{\mathbf{B}}(t) = \left\lceil \frac{\eta_S \vartheta}{t} \right\rceil \tag{8}$$

with $\vartheta \epsilon [0,1]$. Using this approach, the large initial belief space decreases exponentially with time.

### 3.3.3 Adjusting Belief Space

The individuals selected through the acceptance function defined by equation (8) above. The normative and situational components can thus be updated as under, the function being minimized is assumed to be continuous and unconstrained:

- **Situational Knowledge**: We have assumed that only one element has been kept in the situational knowledge component[22].

$$\mathcal{S}(t) = \{\widehat{\beta}(t+1)\} \tag{9}$$

where

$$\widehat{\beta}(t+1) = \begin{cases} min_{l=1,2,\ldots \eta_{B(t)}}\{\alpha_l(t)\} \; if \; f\left(min_{l=1,2,\ldots \eta_{B(t)}}\{\alpha_l(t)\}\right) < f\left(\widehat{\beta}(t)\right) \\ \widehat{\beta}(t) \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{10}$$

- **Normative Knowledge:** The interval update is as follows

$$\alpha_{min,j}(t+1) = \begin{cases} \alpha_{lj}(t) \; if \; \alpha_{lj}(t) \leq \alpha_{min,j}(t) \; or \; f(\alpha_l(t)) < \mathbb{L}_j(t) \\ \alpha_{min,j}(t) \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{11}$$

$$\alpha_{max,j}(t+1) = \begin{cases} \alpha_{lj}(t) \; if \; \alpha_{lj}(t) \geq \alpha_{max,j}(t) \; or \; f(\alpha_l(t)) < \mathbb{U}_j(t) \\ \alpha_{max,j}(t) \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{12}$$

$$\mathbb{L}_j(t+1) = \begin{cases} [f(\alpha)_l(t)) \; if \; \alpha_{lj}(t) \leq \alpha_{min,j}(t) \; or \; f(\alpha_l(t)) < \mathbb{L}_j(t) \\ \mathbb{L}_j(t) \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{13}$$

$$\mathbb{U}_j(t+1) = \begin{cases} [f(\alpha)_{lj}(t)) \; if \; \alpha_{lj}(t) \geq \alpha_{max,j}(t) \; or \; f(\alpha_l(t)) < \mathbb{U}_j(t) \\ \mathbb{U}_j(t) \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{14}$$

### 3.3.4 *Influence Function*

The individuals in the population are adjusted using beliefs to conform closer to the global beliefs. These adjustments are realized via influence functions. The two levels of Cultural Algorithm communicate through the acceptance function and the influence function.

The flow chart for Cultural Algorithm is shown in Figure 3. In this algorithm, the belief space and the population space are firstly initialized. Then, through successive iteration the algorithm repeats its processing for each generation until a termination condition is achieved. Individuals are evaluated using the Fitness function[23].
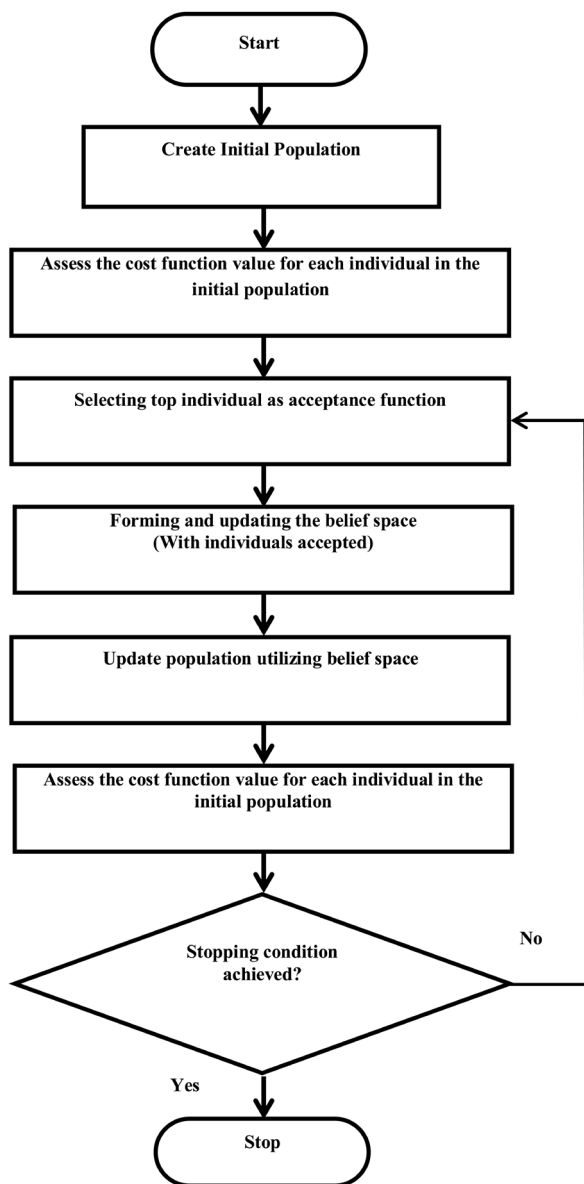


**Figure 3.**  Flowchart for cultural algorithm.

## 4.  Fitness Functions

The objective of a fitness function is to enable the system to identify set of optimal parameters. A CR achieves cognition through a process of sensing, learning and finally adapting to the information gained through the first two processes. In order to adapt itself efficiently to the surrounding environment, it is imperative that the various parameters be tuned to optimum values. These parameters may include power consumption, Bit Error Rate (BER), throughput, spectrum efficiency etc. For achieving desired output, a CR has to adjust these parameters dynamically with the prevailing channel conditions. Hence both single objective and multi objective fitness factors need to be incorporated in the overall design of a cognitive engine. EAs require a scalar fitness functions, providing single scalar value for a given set of parameters. In absence of global criteria, for these parameters the objectives may even be aggregated into a scalar function as this may yield a single scalar solution for the overall fitness function. Depending upon the existing channel conditions, a weight may be attached to specific parameter objectives in such a manner that the sum total of all the weights attached to various parameter objectives is equal to 1. For a multi objective fitness function of the parameter set solution $x$ by the following weighted sum of $N$ objectives[24]:

$$f(x) = \sum_{i=1}^{N} w_i f_i(x) \tag{15}$$

With $w_1$, $w_2$, $w_n$ satisfying the following constraints:
$$1 \geq w_i \geq 0 \ for \ i = 1,2,\dots n \ .$$

$$w_1 + w_2 + \dots w_n = 1 \tag{16}$$

For a given environment, whenever we intend to seek a single optimal solution, it implies that the direction of search of the EA in use is fixed, and in such cases each of the balance performance objectives will be tuned through constant allocation of weights such that these weights guide the algorithm in the direction of search to yield best solution. In case, the allocation of weights is variable, the algorithm may get steered in varying directions thereby yielding different results. To assimilate this aspect better, let us consider a radio set which is working in an environment wherein spectral efficiency is of paramount importance. In order to achieve this aim, the

radio set will allocate higher weightage to say modulation type, as higher modulation scheme like 64 QAM are known to have better spectral efficiency. Accordingly balance of the parameters will get tuned in accordance with this modulation scheme so as to achieve desired result. Now in case the channel conditions deteriorate, then use of higher modulation scheme may result into higher BER, which is detrimental to the overall performance of the link. In such cases, the primary aim would be to keep this link intact before it fails due to increased BER conditions. Thus the search direction will have to be modified in a new direction which minimizes the overall BER of the link. Thus reallocation of weights may be required together with switch to lower order modulation schemes like QPSK and BPSK which can sustain through a noisy environment.

## 4.1 Single and Multiple Objective Functions

Single objective function for an individual objective can be derived using weighted sum approach. However, if several single objective functions are cascaded such that the cumulative weight of the participating objective functions is equal to one, we get a multiple objective function. In the succeeding paragraphs of our paper, we shall define fitness function for some of the commonly used performance objectives[24].

## 4.2 Minimizing Overall BER

In order to minimize the overall BER of a link, certain transmission and environmental parameters need to be defined. The transmission parameters considered for minimizing the overall BER include Bandwidth, Transmission Power, Modulation Type and Modulation Index whereas the environmental parameters include Received Signal Strength, Path Loss and Noise Power. The calculation of BER will depend primarily on two aspects, modulation scheme and the channel type, as different modulation schemes employ different formulae to calculate BER. If energy per bit is denoted by $E_b$, and noise power spectral density by $N_0$ the ratio $E_b/N_0$ may be utilized for computing BER. If $S$ denotes the signal power of the transmitted signal, $R_s$ denote the symbol rate and $m$ denotes the number of bits or modulation index then energy per bit can be written as[24]:

$$E_b = \frac{S}{R_s \times m} \qquad (17)$$

The value of noise per hertz and noise power over complete bandwidth can be found using following relations:

$$N_0 = K\,T$$
$$N = N_0 B \qquad (18)$$

Where $K$ denotes Boltzmann's Constant, $T$ denotes the system noise temperature and $B$ denotes bandwidth. The ratio $E_b/N_0$ can then be written as

$$\frac{E_b}{N_0} = 10\,log_{10}\left(\frac{S\,B}{R_s\,mN}\right) = 10log_{10}\left(\frac{S}{N}\right) + 10log_{10}\left(\frac{B}{R_s\,m}\right) \qquad (19)$$

Equation (19) can be utilized to calculate $E_b/N_0$ for QAM, PSK and FSK modulation schemes in AWGN channel. Table 3 lists out the probability of error $P_{be}$ for some of the commonly employed modulation schemes.

A valid range for a fitness function would be between 0 and 1, hence the BER here is normalized with its worst case scenario (considered as 0.5) and arriving at our desired fitness function:

$$f_1(min\,_{\downarrow}BER) = 1 - (\square log\square_{\downarrow}10\,(0.5)$$
$$- \square log\square_{\downarrow}10\,(P_{\downarrow}be\,))/(\square log\square_{\downarrow}10\,(0.5)$$
$$- \square log\square_{\downarrow}10\,(\square 10\square^{\dagger}(-6)\,)) \qquad (20)$$

Here $10^{-6}$ has been assumed as the best possible value of BER and any value lower than this would be rounded to $10^{-6}$.

**Table 3.** Probability of bit error

| Ser No | Modulation Type | Pbe |
|---|---|---|
| 1 | BPSK | $P_{be} = Q\left(\sqrt{\frac{E_b}{N_0}}\right)$ |
| 2 | M-ary PSK | $P_{be} = \frac{2}{log_2(m)}Q\left(\sqrt{\left(2log_2(m)\left(\sqrt{\frac{E_b}{N_0}}\right)\right) \times Sin\left(\frac{\pi}{m}\right)}\right)$ |
| 3 | M-ary QAM | $P_{be} = \frac{4}{log_2(m)}\left(1 - \frac{1}{\sqrt{m}}\right)Q\left(\sqrt{\frac{3 \times log_2(m)}{m-1}\left(\frac{E_b}{N_0}\right)}\right)$ |

## 4.3 Throughput Maximisation

For achieving desired throughput over a link, certain transmission parameters play a pivotal role. These

parameters include Modulation Type, Modulation Index, Bandwidth, Frame Length, Symbol Rate, Coding rate and Time Division Duplexing. Throughput implies amount of data transmitted successfully over a link or network per unit time. For real time applications like video conferencing, it is always desired to have higher throughput for unhindered data transmission. In order to achieve this, it is imperative that a strategy be adopted which may minimize the overall packets going in error. The probability of packets in error $P_{pe}$ can expressed with the help of following expression[23]:

$$P_{pe} = 1 - (1 - P_{ber})^L \qquad (21)$$

When channel conditions are conducive of transmission, i.e. when SNR is high, larger frame size can pay richer dividends as the transmission is relatively error free. At lower values of SNR, more number of packets are in error thus sending larger frames would render large amount of data loss thereby degrading the system throughput. Researchers have shown that significant improvements in the system throughputs can be achieved by altering the frame size as per the prevailing SNR conditions. A relation between frame sizes (L), BER and throughput (G) is expressed as under:

$$G = m * R_s * \frac{L}{L + O + H} * (1 - P_{ber})^{L+O}$$
$$= R_b * \frac{L}{L + O + H} * (1 - P_{ber})^{L+O} \qquad (22)$$

Where $R_b$ represents the raw bit rate in bits per sec, $H$ is the MAC and IP layer overhead at value of 40 bytes, $O$ represents the physical layer overhead at 52.5 bytes. After normalisation we arrive at our expression for max throughput:

$$f_1(\max throughput) = L/(L + O + H)$$
$$* (1 - P_{ber})^\uparrow (L + O) * R_c * TDD \qquad (23)$$

## 4.4 Power Consumption Minimisation

Power consumption assumes vital importance especially in context of mobile radio platform which have to sustain themselves over secondary batteries for large durations. An inefficient power management scheme may result a radio running out of battery even under conditions when same link quality could have been achieved with a much lower power. Power minimisation would also be beneficial when we want to reuse a frequency to avoid interference[21].

$$f_1 = \frac{(P_{max} + B_{max\ \square}) - (P + B)}{P_{max} + B_{max\ \square}} \qquad (24)$$

Higher processing power required due to computational complexities and transmission overheads also leads to higher power consumption. Parameters like increased symbol rate and depth of modulation may result in increased computation complexity. A generalised expression for power consumption due to increased computational complexity. The fitness score in this case can again be obtained through normalisation.

$$f_2 = \frac{\log_2(m_{max\ \square}) - \log_2(m)}{\log_2(m_{max\ \square})} \qquad (25)$$

$$f_3 = \frac{R_{S_{max\ \square}} - R_s}{R_{S_{max\ \square}}} \qquad (26)$$

Combining equations (24), (25) and (26) into linear objective function

$$f_1(\min \downarrow pwr) = 1 - [\alpha * ((P_\downarrow max + B_\downarrow \mathbf{max}) - (P + B))/$$
$$(P_\downarrow max + B_\downarrow max) + \beta * (\square \log \square_\downarrow 2\ (m_\downarrow max)$$
$$- \square \log \square_\downarrow 2\ (m))/(\square \log \square_\downarrow 2\ (m_\downarrow max))$$
$$+ \lambda * (R_\downarrow (S_\downarrow \mathbf{max}) - R_\downarrow S)/R_\downarrow (S_\downarrow max)] \qquad (27)$$

here $\alpha$, $\beta$ and $\lambda$ represent the weighting factors of the objective functions.

## 4.5 Minimizing Spectral Interference

In a CRN, whenever primary user (PU) and secondary user (SU) co-exist there is always a likelihood of interference being caused by the SU to the transmissions of PU. The parameters that may gauge the amount of spectral interference being caused include transmit power, bandwidth and time division depleting. We can write the interference equation as:

$$f_{interference} = P * B \qquad (28)$$

Equation (28) suggests that the interference potentially increases with the increase in bandwidth and transmit power, resulting in increased spectral leakage and more raw transmit power that can interfere with other communication system. Thus normalized spectral interference can be expressed as[18]:

$$f_{\downarrow}(\min \downarrow interference) = 1 - ((P * B * TDD) -$$
$$(P_{\downarrow}min * B_{\downarrow}min * 1))/(P_{\downarrow}max * B_{\downarrow}max * 100)$$

(29)

## 4.6 Maximizing Spectral Efficiency

One of the objectives of any communication transmission system is to maximize the information that can be exchanged over the network. This functionality is achieved through maximization of spectral efficiency, which is directly related to the bandwidth and channel information carrying capacity. Maximizing spectral efficiency implies maximum transportation of information across a relatively smaller bandwidth, one of the way of achieving this is by increasing modulation index keeping the bandwidth in use to be constant[24–25].

$$f_{spectral}^{max} \; efficiency = \frac{\frac{m * R_S}{B}}{\frac{m_{max} * R_{S_{max}}}{B_{min}}}$$
$$= \frac{m * R_S * B_{min}}{B * m_{max} * R_{S_{max}}}$$

(30)

## 4.7 Multi-Carrier Objective Function

For systems employing multiple independent carriers, the objective functions are averaged over the total number of carriers[24–25].

$$f_{\downarrow}(\min \downarrow BER) = 1 - (\Box log\Box_{\downarrow}10\,(0.5))/(\Box log\Box_{\downarrow}10\,((P_{\downarrow}be)^{-}))$$

(31)

Where $\overline{P_{be}}$ is the average BER over N independent subcarriers.

$$f_{\downarrow}(\max \downarrow tp) = (\Sigma_{\downarrow}(i = 1)^{\uparrow}N\boxtimes(L_{\downarrow}i/(L_{\downarrow}i + O + H)$$
$$* (1 - P_{\downarrow}(\Box BER\Box_{\downarrow}i))^{\uparrow}(L_{\downarrow}i + O) * R_{\downarrow}(c_{\downarrow}i) * \Box TDD\Box_{\downarrow}i))/N$$ (32)

$$f_{\downarrow}(\min \downarrow pwr) = [1 - \alpha * (\Sigma_{\downarrow}(i = 1)^{\uparrow}N\boxtimes\Box(P_{\downarrow}max + B_{\downarrow}\mathbf{max}) -$$
$$(P_{\downarrow}i + B)\Box)/(N * P_{\downarrow}max + B_{\downarrow}\mathbf{max}) + \beta * (\Sigma_{\downarrow}(i = 1)^{\uparrow}N\boxplus\Box\Box log\Box_{\downarrow}2$$
$$(m_{\downarrow}\mathbf{max}) - \Box log\Box_{\downarrow}2\,(m_{\downarrow}i)\,\Box)/(N * \Box log\Box_{\downarrow}2\,(m_{\downarrow}\mathbf{max})) + \lambda * (\Sigma_{\downarrow}(i = 1)$$ (33)

$$f_{\downarrow}\min\rightarrow interference = 1 - (\Sigma_{\downarrow}(i = 1)^{\uparrow}N\boxtimes((P_{\downarrow}i * B_{\downarrow}i * \Box TDD\Box_{\downarrow}i)$$
$$- (P_{\downarrow}min + B_{\downarrow}min + 1)))/(N * (P_{\downarrow}max + B_{\downarrow}max + 100))$$ (34)

$$f_{spectral}^{max} \; efficiency = \frac{\Sigma_{i=1}^{N}\left(\dfrac{m_i * R_{S_i} * B_{min}}{B * m_{max} * R_{S_{max}}}\right)}{N}$$

(35)

In the average fitness scores listed above, each carrier's fitness score is summed together and divided by total number of subcarriers (N).

## 4.8 Multiple Objective Goals

As mentioned earlier, multiple objective functions for multiple carriers can be formed by single objective equations as under:

$$f_{\downarrow}multicarrier = w_{\downarrow}1 * (f_{\downarrow}(\min \downarrow BER)) + w_{\downarrow}2 *$$
$$(f_{\downarrow}(\max \downarrow tp)) + w_{\downarrow}3 * (f_{\downarrow}(\min \downarrow pwr)) + w_{\downarrow}4 *$$
$$(f_{\downarrow}(\min \downarrow interference)) + w_{\downarrow}5 *$$
$$(f_{\downarrow}(\max \downarrow spectralefficiency))$$

(36)

Weights $w_1$, $w_2$, $w_3$, $w_4$ and $w_5$ define the search direction of the EA in use. Typical weights for some of the common performance objectives are shown in Table 4[26].

Table4. Weighting scenarios

| Ser No | Scenario | Weight Vector $w_1$, $w_2$, $w_3$, $w_4$, $w_5$. |
|---|---|---|
| 1 | Low Power Mode (Minimize power) | 0.10, 0.20, 0.45, 0.15, 0.10. |
| 2 | Emergency Mode (Minimize BER) | 0.50, 0.10, 0.10, 0.10, 0.20. |
| 3 | Dynamic Spectrum Access Mode (Minimize Interference) | 0.10, 0.20, 0.10, 0.50, 0.10. |
| 4 | Multimedia Mode (Maximize Throughput) | 0.15, 0.50, 0.10, 0.15, 0.10. |
| 5 | Balanced Mode | 0.20, 0.20, 0.20, 0.20, 0.20. |

# 5. Simulation and Results

In this section we have compared the simulation results of the three proposed algorithms i.e. PSO, GA and CA. OFDM is been used within an infrastructure based networks where the cluster heads share environment information with the Central Spectrum Manager (CSM) or the Fusion Centre (FC). The environment parameters like BER, SNR, losses etc. are supplied by the cluster heads to the Fusion Centre, which then decides the transmission parameters like transmit power, modulation type and modulation index etc. The attenuation per channel has been considered random and is same is utilized for calculation of SNR at the receiver which in turn can be used to calculate the BER. Same random values are used while comparing all three algorithms.

For the purpose of simulation, certain assumptions have been made. The CR pairs analysed are in the configuration of 5/10/20/30 with each pair being allocated with a single subcarrier. The allocation of subcarriers or frequency bands to the various CR pairs is carried out by the FC without frequency reuse. The channel state information is exchanged with the FC over a reporting channel. The entire available bandwidth has been divided equally amongst all the subcarriers. The transmit power for each sub carrier has been kept in the range of 5 to 250 mW and the modulation type considered is BPSK, 4/16/64 QAM. The efficiency of each algorithm is adjudged based on two factors. Firstly, Time of Convergence and secondly quality of results obtained for 5/10/20/30 sub carriers over 5/10/20/40/100 iterations. The parameters of each algorithm are so chosen such that the computational complexity of each algorithm is approximately the same. The details of these parameters have been summarised in Table 5. Figure 4 shows the comparative analysis of the time of convergence computed for 5/10/20/30 CR pairs over 20/40/100 iterations for PSO, GA and CA.
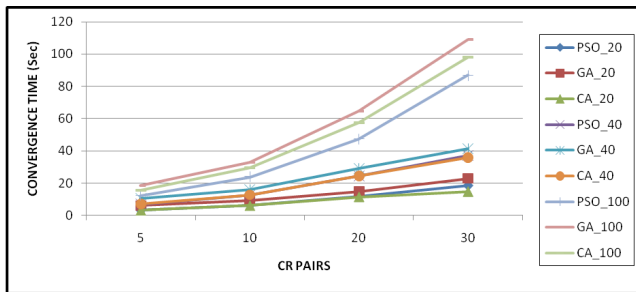


**Figure 4.** Comparison of convergence time.

**Table 5.** Parameters for various algorithms

| Particle Swarm Optimisation | |
|---|---|
| Swarm Size | 40 |
| Weight of Personal Best | 1.414 |
| Weight of Global Best | 2.414 |
| Inertia | 0.7 |
| Max Iterations | 500 |
| Genetic Algorithm | |
| Population Size | 40 |
| Crossover Faction | 0.8 |
| Mutation Faction | 0.01 |
| Maximum Generations | 500 |
| Selection Function | Roulette Wheel |

| Cultural Algorithm | |
|---|---|
| Population Size | 40 |
| Alpha | 0.3 |
| Accept | 0.35 |
| Maximum Generation | 500 |
| Belief Space Used | Normative and Situational |

From the data given of Figure 4, it is evident that there is no linear relationship between the number of CR pairs and time of convergence, further, as the number of iterations increases the time taken by the algorithm to converge increases exponentially. When the number of iterations is less (i.e. upto 40 iterations) the time for convergence is least for CA however as the number of iterations increase (upto 100), PSO converges faster. The convergence for GA is relatively sluggish as compared to PSO and CA.

Figure 5 shows the comparison of the average fitness score for the three algorithms for 5/10/20 CR pairs over 100 iterations.
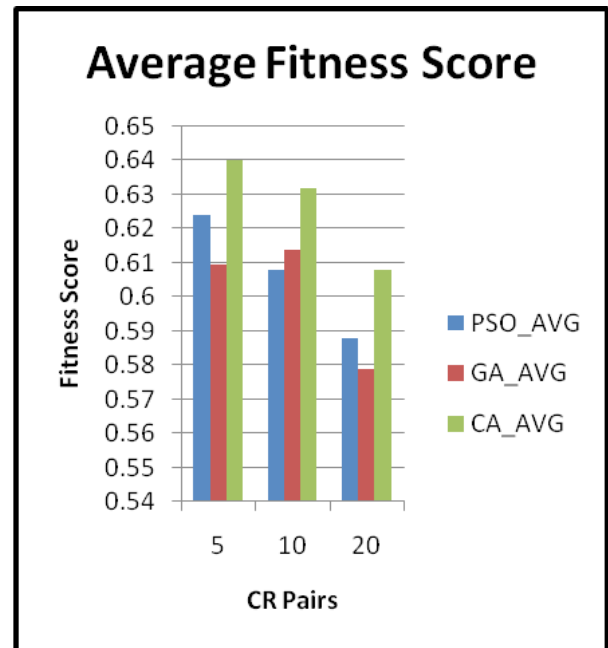


**Figure5.** Fitnesss core over 100 iterations.

Figure 6 compares the performance of the three algorithms based on average fitness scores across various modes. These fitness scores have been obtained by averaging individual fitness scores for Low Power Mode (LPM), Emergency Mode (EM), Multimedia Mode (MM) and

Balanced Mode (BM) for each algorithm. It is evident that CA has much better fitness scores followed by PSO and GA.
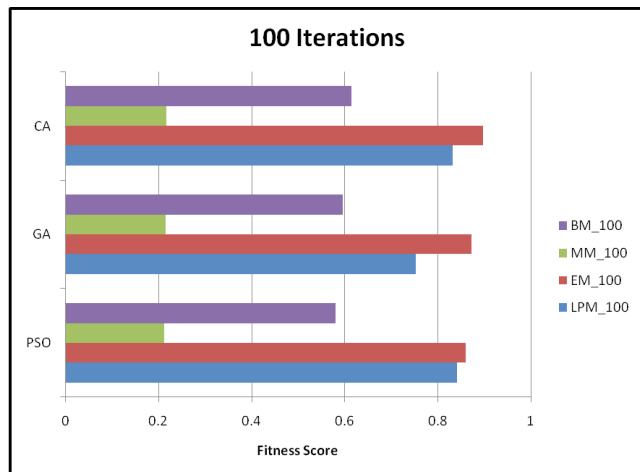


**Figure 6.** Average fitness score.

In Table 6 the fitness score for CA under various operating modes for 5/10/20/30 CR pairs over 5/10/40/100 iterations are given.

**Table 6.** Fitness score of cultural algorithm for various operating modes

| No of CR Pairs | Modes | No of Iterations | | | |
|---|---|---|---|---|---|
| | | 5 | 10 | 40 | 100 |
| 5 | LPM | 0.79 | 0.8 | 0.823 | 0.832 |
| | EM | 0.866 | 0.82 | 0.872 | 0.898 |
| | MM | 0.287 | 0.273 | 0.213 | 0.218 |
| | BM | 0.571 | 0.57 | 0.616 | 0.615 |
| 10 | LPM | 0.657 | 0.65 | 0.812 | 0.814 |
| | EM | 0.828 | 0.85 | 0.819 | 0.878 |
| | MM | 0.278 | 0.283 | 0.208 | 0.215 |
| | BM | 0.571 | 0.562 | 0.568 | 0.619 |
| 20 | LPM | 0.632 | 0.65 | 0.756 | 0.828 |
| | EM | 0.783 | 0.82 | 0.824 | 0.832 |
| | MM | 0.266 | 0.27 | 0.207 | 0.207 |
| | BM | 0.495 | 0.555 | 0.565 | 0.566 |

Figure 7 (a) to (d) below highlights the performance comparison of a CRN working on PSO, CA and GA. The scenario is simulated for a total of 10 CR pairs over 40 iterations. The results are indicative of the fact that CA is

a promising solution for implementation in CRN owing to its fast convergence and better fitness factor.

Similar results have also been computed for 10 CR users with 100 iterations in Figure 8(a) to (d). The results also indicate that CA is a robust approach when subjected to operate under varying environmental and transmission/operating parameters, and hence can be used even if parameters like global best and personal best are not available from the environment, further, CA always endeavors to better itself with each iteration, resulting in a much refined output which is suitably habituated with the surrounding environment.
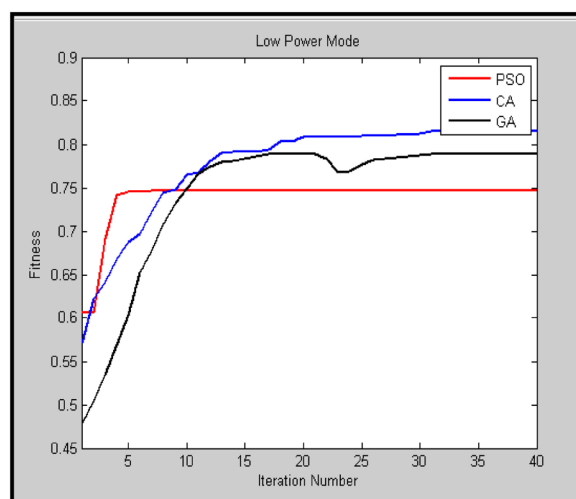


(a1)
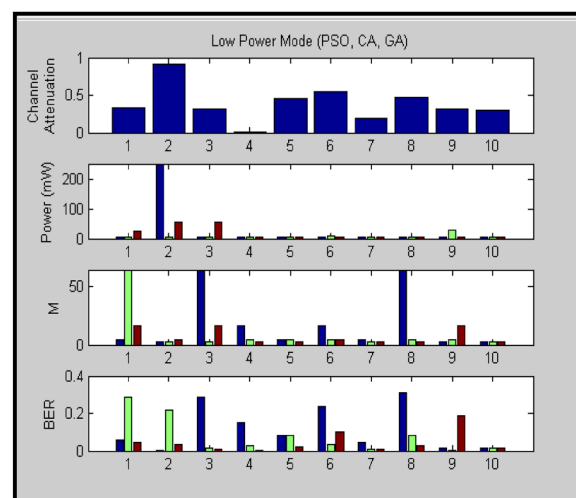


(a2)

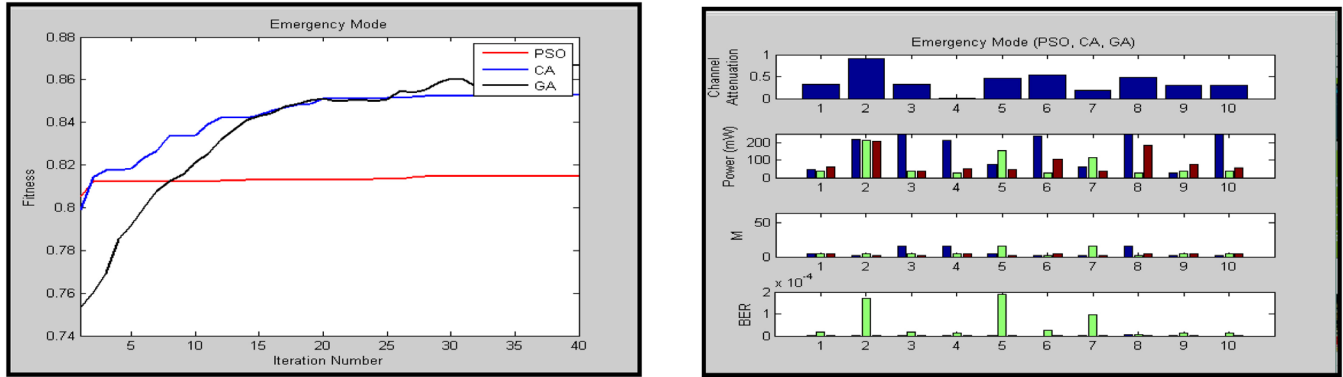**Figure 7(a and b).** Low power mode: 10 CR pairs over 40 iterations.

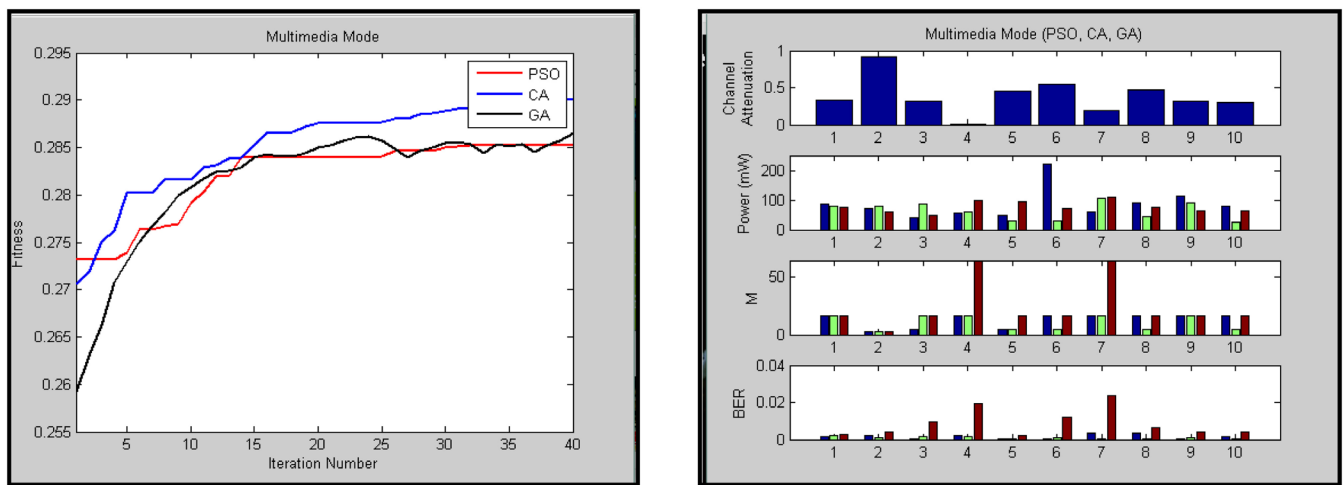**Figure 7(b1 and b2).** Emergency mode 10 CR pairs over 40 iterations.



**Figure 7(c1 and c2).** Multimedia mode 10 CR pairs over 40 iterations.
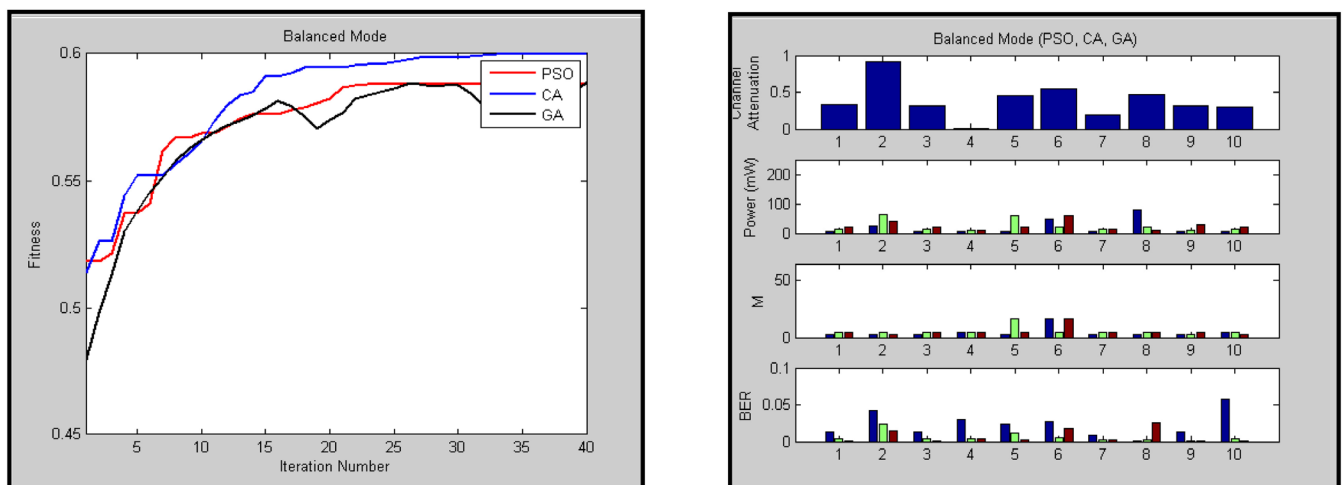


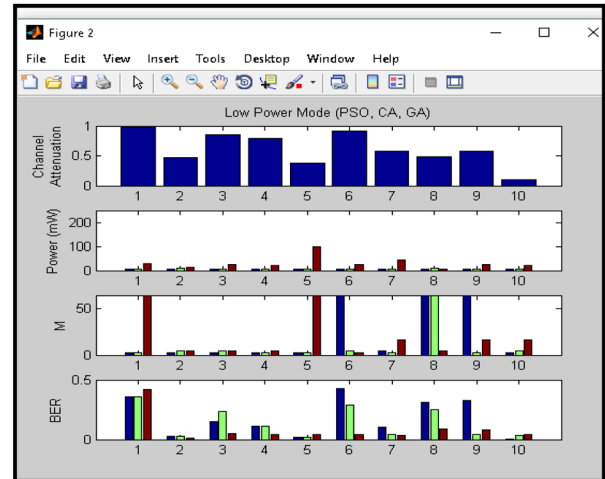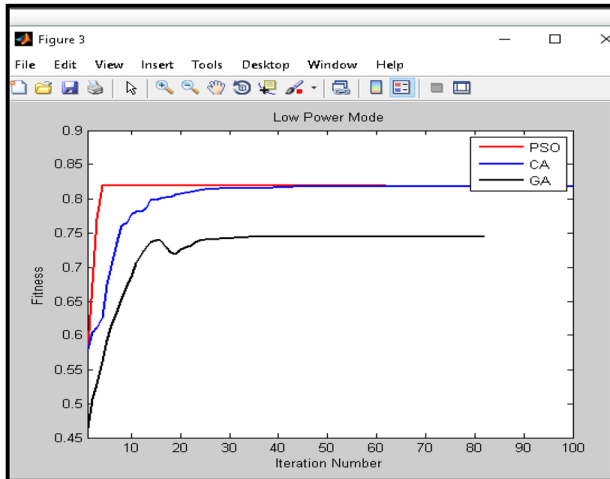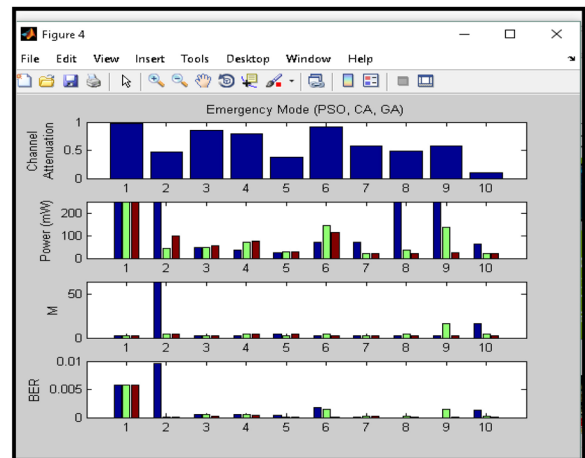**Figure 7(d1and d2).** Balanced mode 10 CR pairs over 40 iterations.

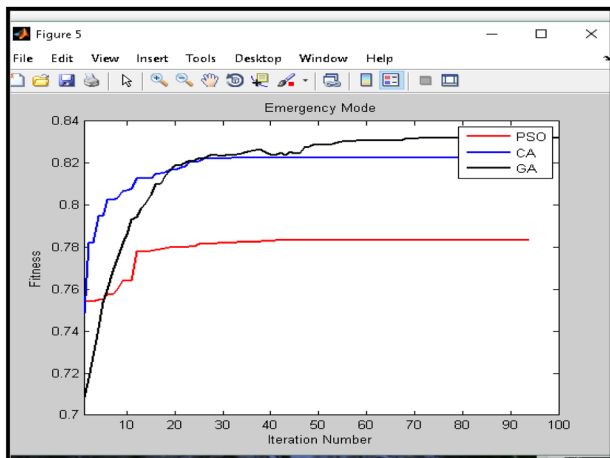**Figure 8(a1 and a2).** Low power mode 10 CR pairs over 100 iterations.



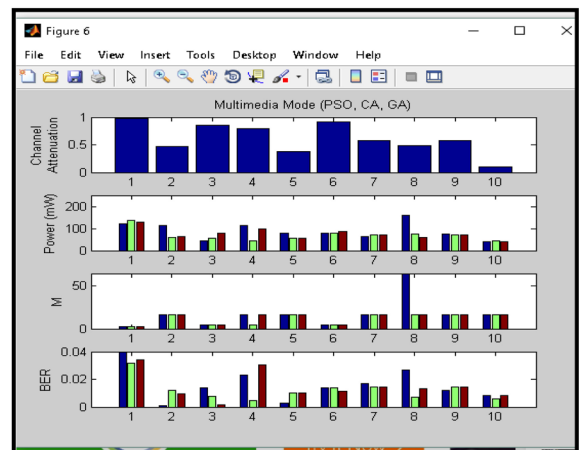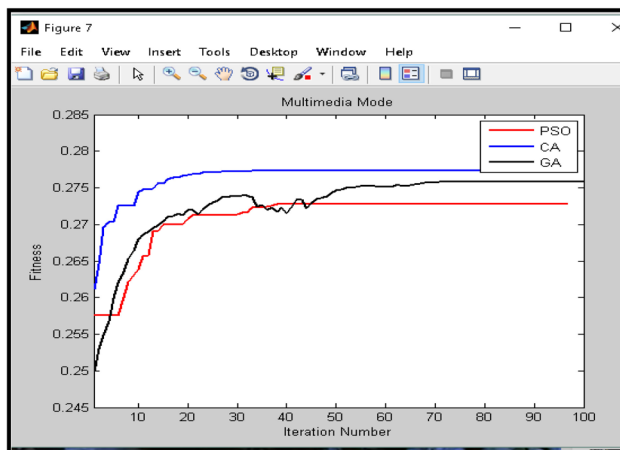**Figure 8(b1 and b2).** Emergency mode 10 CR pairs over 100 iterations.



**Figure 8(c1 and c2).** Multimedia mode: 10 CR pairs over 100 iterations.
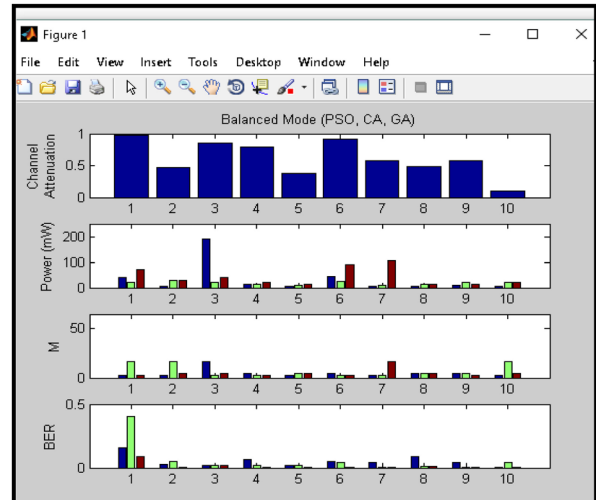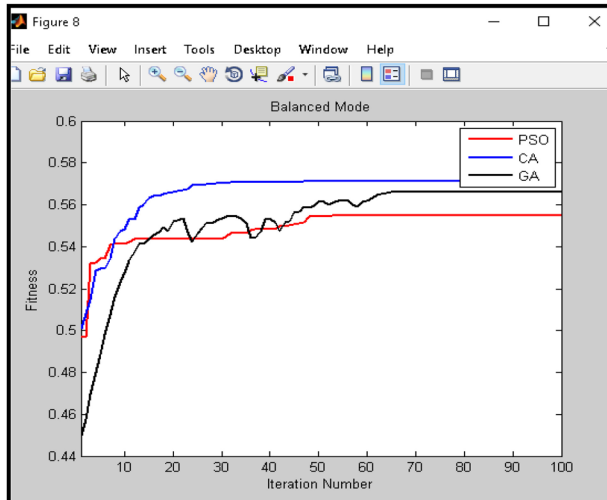
**Figure 8(d1 and d2).** Balanced mode 10 CR pairs over 100 iterations.

# 6. Conclusion

Cultural Algorithm is used for Cognitive Engine design. The results have been compared with the other commonly used Evolutionary Algorithms. A multi-carrier system has been simulated here to replicate the complex environmental scenarios. CA is extremely effective as it shows better convergence time and effective fitness scores which makes it a suitable candidate to be explored for cognitive engine design. The scope of CR can further be extended to the fourth and fifth generation of mobile communications[27], wherein the CR approach can be adopted to enhance the overall data rates.

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