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Survey Paper

Comparative performance analysis of evolutionary algorithm based parameter optimization in cognitive radio engine: A survey

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ABSTRACT

One of the important features of the cognitive radio engine is to adapt the parameters of radio to fulfill certain objectives in a time varying wireless environment. In order to achieve this adaptation, six evolutionary algorithms are employed for optimizing the predefined fitness functions in the radio environment. The performance of genetic algorithm, particle swarm optimization, differential evolution, bacterial foraging optimization, artificial bee colony optimization and cat swarm optimization algorithm in different modes of operation are studied in detail. Each algorithm is tested in single and multicarrier communication system in order to acknowledge the advantage of multicarrier communication systems in wireless environment. The spectral interference introduced by the cognitive user into the primary user's band and that introduced by the primary user into the cognitive user's band are also investigated. The performance of different algorithms are compared using convergence characteristics and four statistical metrics.

1. Introduction

Over the past decades, the demand for electromagnetic spectrum has increased exponentially due to the popularity of wireless devices such as smart phones and mobile devices. Since most of the usable spectrum is already allocated, the demand for more spectrum is a huge challenge for researchers worldwide. Previous studies have shown that 90% of the allocated spectrum is either unused or underutilized [1,2]. So the solution lies in the efficient usage and higher utilization of the available spectrum. The present spectrum policy uses static spectrum allocation which has resulted in underutilization of the spectrum [1]. Most of the spectrum bands are only used in some areas and for some part of time. Hence researchers have proposed a dynamic spectrum allocation approach which allocates spectrum dynamically depending on the need at a particular time or location. Cognitive radio (CR) uses this technique to provide better spectrum efficiency and utilization.

The CR is a wireless radio that senses its electromagnetic environment and dynamically adapts its operational parameters to achieve the best system performance. The CR was first proposed by Mitola and Maguire [3] as a software radio with radio knowledge based reasoning about radio etiquettes such as RF bands, protocols, and patterns. The important feature of the CR includes sensing, learning and adapting its operating parameters depending on the radio environment, primary and secondary user requirements, availability of spectrum, local radio protocols, etc. Currently most of the licensed bands use a single communication technology. But the CRs use a combination of different technologies to get the best performance at a

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particular instant of time. This requirement poses a major challenge for the industry and academic researchers. The other major challenges include spectrum sensing, architecture, engine design, cognitive network security, etc. Recently the CRs have attracted the interests of various researchers [4,5] and led to applications such as wireless innovation alliance and IEEE 802.22 standard in wireless regional area network [6].

This paper focuses on the challenges in designing an efficient CR engine. The CR engine configures the radio system parameters to provide the best performance with respect to a predefined set of objectives and constraints. Since the objectives in a wireless environment are multiple in number, the problem of CR engine design can be formulated as a multiobjective optimization problem. The literature on the design of CR engine can be broadly categorized based on single and multicarrier communication system, and single and multiobjective optimization.

1.1. Single carrier communication system based CR engine

The techniques mentioned in this section describe the CR engine design only for single carrier communication systems. These techniques can be further categorized based on single and multiobjective optimization.

1.1.1. Single objective weighted sum optimization

In this case, the multiple objectives are weighted independently to generate a single objective fitness function which is simple and easy to implement from hardware point of view. The weights assigned to the objective functions mostly correspond to three modes of operation: emergency, low power and multimedia. The first CR engine was designed by the researchers at Virginia Tech [7,8]. They have used genetic algorithm (GA) to adapt the radio parameters of the software defined radio in a time varying radio environment. Rieser [9] has proposed a GA based CR engine in which the objectives are weighted differently depending on the user requirement and condition of the radio link. This weighted sum GA based design considered code rate, operating frequency, modulation type, etc. as the design parameters and frame error rate, transmit power, spectral efficiency, etc. as the design objectives. Hauris [10] has used the GA for changing the radio parameters of CRs in autonomous vehicles which travel through rapidly changing radio environments. Kim et al. [11] have designed a software to model a CR system. They have incorporated spectrum sensing ability and a GA based CR engine into the software. Zhang and Xie [12,13] have proposed a CR engine model using neural network in which the learning and adaptation of the CR is based on the fixed as well as the variable factors. The sensitivity of different transmission parameters on the performance of a GA based CR engine has been studied in detail by Newman and Evans [14]. An ant colony optimization (ACO) based CR engine design is proposed by Zhao et al. [15]. Huynh and Lee [16,17] have used a two-dimensional structure for chromosome's implementation while optimizing the parameters of CR engine.

1.1.2. Multiobjective optimization

Park et al. [18] have proposed a goal-Pareto based nondominated sorting genetic algorithm (GBNSGA) for the CR engine design. They have validated the application of the GBNSGA in a code division multiple access (CDMA) 2000 forward link by using a realistic scenario in a Rician channel. A multiobjective immune GA (MIGA) based CR is proposed by Yong et al. [19]. They have used the MIGA for designing a control module based on the IEEE 802.11a physical platform.

1.2. Multicarrier communication system based CR engine

The research activities in mobile communication have shown that multicarrier communication systems provide higher data rate and robustness to losses in the wireless channel. Orthogonal frequency division multiplexing (OFDM) is one of the multicarrier systems which provides flexible resource allocation among cognitive users. Any subcarrier in the OFDM can be deactivated easily by feeding zero power to it. This feature makes the OFDM a good candidate for the CRs [20]. A lot of studies have been carried out for resource allocation in OFDM systems [21–23].

1.2.1. Single objective weighted sum optimization

Newman et al. [24] have designed a weighted sum GA based CR engine for OFDM based transceivers. They have derived a set of objective functions for guiding the search direction of the GA. They have also demonstrated the trade off between the convergence time and size of the search space of the GA. The CR engine design based on different variants of the GA is also proposed in literature [14, 25–29]. Most of the OFDM based CR engine designs do not consider the existence of primary users. But in a real time scenario, the primary and the secondary users exist simultaneously and use different communication access technologies too. This leads to mutual interference which ultimately degrades the performance of both the users [20]. In literature, mutual interference in the OFDM based CR is considered only in single objective optimization problem such as capacity maximization [30–32] while ignoring secondary user's performance.

The recent studies have shown that the new evolutionary algorithms (EAs) perform better than the GA in terms of quality of solution, convergence time and computational complexity. Zhao et al. [33] have proposed a CR engine design based on binary particle swarm optimization (PSO). They have shown that the PSO based CR engine design performs better than a GA based counterpart in terms of fitness value, convergence speed and stability. Afterwards, a PSO based CR engine in real number space [34] has been proposed to improve the performance in decision making. El-Khamy et al. [35] have shown that a hybrid of binary-coded PSO and GA (HBPGA) for optimizing the radio parameters of a CR performs better than the conventional GA and PSO. Waheed and Cai [36] have used the binary ACO for adapting the parameters of a CR in multicarrier environment. They have shown that the binary ACO based CR engine design provides a better solution than a GA based counterpart. Waheed and Cai [37] have compared the performances of the binary PSO, binary ACO and GA in the CR engine framework and found the binary PSO to be a better candidate among the three algorithms. Huang et al. [38] have proposed a CR learning engine based on support vector machine and demonstrated its performance on 802.11a protocol platform. Chen and Wen [39] have introduced cross entropy method for optimizing the parameters in the CR engine design. They have demonstrated that their proposed method performs better than the conventional PSO based CR engine design. Pei-Pei et al. [40] have used a weighted sum based GA for resource allocation in an OFDM based CR by considering bit error rate, throughput and transmission power as objective functions. However they have not considered the spectral interference introduced by the secondary user into the primary user's band. Di et al. [41] have suggested the use of immune theory as a priori knowledge to guide the EAs in optimizing the parameters of a CR engine. Zhang et al. [42] have introduced a binary quantum-behaved PSO for optimizing the parameters of a CR engine. Artificial bee colony (ABC) algorithm based parameter adaptation for a CR engine has been proposed by Pradhan [43].

1.2.2. Multiobjective optimization

El-Saleh et al. [44] have proposed an adaptive CR decision engine based on a multiobjective hybrid GA to determine the optimal radio parameters for a single carrier system. Chen et al. [45] have proposed several schemes such as population adaptation, variable quantization, variable adaptation, multiobjective GAs, etc. to enhance the performance of a GA based CR engine. Tosh et al. [46] have suggested the use of nondominated sorting based genetic algorithm to determine the necessary transmission parameters of a CR for a multicarrier system in different scenarios. For designing a CR engine, Pradhan and Panda [47] have shown the performances of four state of the art multiobjective evolutionary algorithms (MOEAs), i.e. nondominated sorting genetic algorithm, multiobjective particle swarm optimization, multiobjective bacterial foraging optimization and multiobjective cat swarm optimization. However the complexity involved in multiobjective optimization and hardware constraints have restricted the usage of the MOEAs in real time applications. In addition, the high speed, small size, compatibility, etc. makes the design of a CR engine a big challenge for researchers worldwide.

The present study provides a generalized approach to solve the CR engine design problem using six popular EAs. The quantitative analysis of the simulation results are carried out using different performance metrics. The two types of interference commonly encountered in a wireless environment have been considered. The spectral interference introduced by the cognitive user into the primary user's band and vice versa are investigated. The possible real time scenarios in a time varying wireless environment are also taken into account during the investigation. The performances of different EAs in single and multicarrier communication systems are compared in each scenario to provide a global view of the CR engine design problem. The qualitative and quantitative analysis of the performances of these algorithms provides an in-depth understanding of the complexities involved in the design problem.

2. Cognitive radio system model and parameters

The CR model assumes that the primary and secondary users coexist in nearby spectrum bands. Fig. 1 depicts a scenario where the central frequency band B is occupied by the primary user and the sidebands are occupied by the cognitive users. In this study, it is assumed that only one primary user is using the central band B and the sidebands are used by a single cognitive user.

For multicarrier based CR, the OFDM is used as the modulation technique for the cognitive user. As shown in Fig. 2, the complete spectrum band available to the cognitive user is divided into N subcarriers keeping $\frac{N}{2}$ subcarriers in each side of the primary user's spectrum band. Each subcarrier has a bandwidth of Δf. The transmission power and bits allocation to subcarriers is carried out by the base station in a dynamic fashion. In most of the practical scenarios, the cognitive user does not know the access technology being used by the primary user. Even if cognitive user is informed that the primary user is using the OFDM, still it is practically very difficult to know the parameters of primary user required to ensure orthogonality. Thus the non-orthogonality between the transmitted signals leads to mutual interference [20]. It this study, it is assumed that the transmitted signal on each subcarrier is a rectangular non-return-to-zero (NRZ) signal as well as the channel is a frequency flat fading channel with known state information at the transmitter.

2.1. Interference introduced by the cognitive user's signal into the primary user's band

The power spectral density (PSD) of the ith subcarrier in the cognitive user's band shown in Fig. 2 is denoted as [48]

$$\phi_i(f) = P_i T_s \left(\frac{\sin \pi f T_s}{\pi f T_s} \right)^2 = P_i T_s \mathrm{sinc}^2(f T_s) \quad (1)$$

where P_i is the total power transmitted by the ith subcarrier in the cognitive user's band and T_s is the symbol duration. If f_i is the intermediate frequency of the ith subcarrier in the cognitive user's band, the PSD is denoted as

$$\phi_i(f) = P_i T_s \left\{ \frac{\sin\ \pi(f - f_i)T_s}{\pi(f - f_i)T_s} \right\}^2 = P_i T_s \mathrm{sinc}^2\{(f - f_i)T_s\} \quad (2)$$

The interference introduced by the ith subcarrier in the cognitive user's band into the primary user's band is given as

$$\begin{aligned} I_i(d_i, P_i) &= \int_{d_i - \frac{B}{2}}^{d_i + \frac{B}{2}} |h|^2 \phi_i(f) df \\ &= P_i T_s \int_{d_i - \frac{B}{2}}^{d_i + \frac{B}{2}} |h|^2 \mathrm{sinc}^2\{(f - f_i)T_s\} df \end{aligned} \quad (3)$$

where h is the channel gain from base station to the primary user, B is the bandwidth of the primary user and d_i is the spectral distance between the ith subcarrier in the

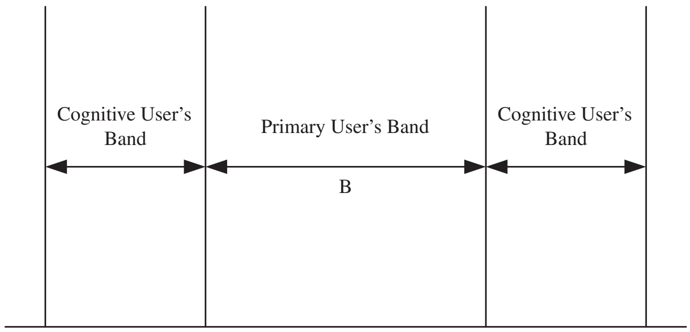

Fig. 1. An example of co-existence scenario of primary and cognitive users in single carrier communication system.

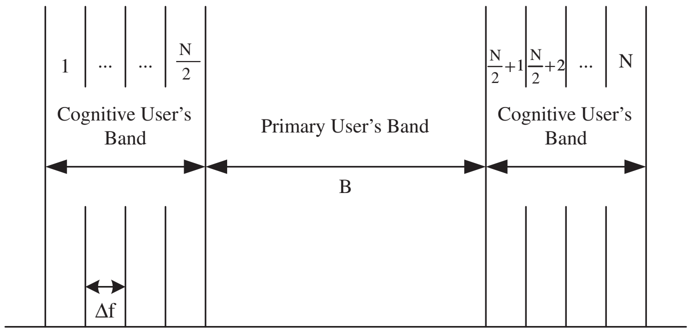

Fig. 2. An example of co-existence scenario of primary and cognitive users in multicarrier communication system.

cognitive user's band and the central frequency of the primary user's band.

2.2. Interference introduced by the primary user's signal into the cognitive user's band

Similar to the previous case, interference is also introduced by the primary user's signal into the cognitive user's band. Since the primary user's interference signal is received by an N-FFT OFDM receiver in the CR, the received signal $r(k)$ passes through a window $w(k)$ in time domain resulting in

$$y(k) = r(k)w(k) \tag{4}$$

The multiplication of two signals in time domain shown in (4) is represented in convolution form in frequency domain as

$$Y(f) = \int_{-\infty}^{\infty} R(\psi)W(f-\psi)d\psi \tag{5}$$

Assuming that the window $w(k)$ is a rectangular window, the PSD [49] of primary user's signal after processing through an N-FFT is given as:

$$E\{I_N(f)\} = \frac{1}{N}\int_{-\infty}^{\infty} \phi_{PU}(f)\left\{\frac{\sin\frac{(f-\psi)N}{2}}{\sin\frac{f-\psi}{2}}\right\}^2 d\psi \tag{6}$$

where $E()$ represents the expectation operator, $E\{I_N(f)\}$ is the periodogram, f is the normalized frequency with respect to sampling frequency, $\phi_{PU}(f)$ is the PSD of the primary user's signal received by the cognitive user. Then the interference introduced by the primary user's signal into the ith subcarrier of the secondary user is denoted as

$$J_i(d_i, P_{PU}) = \int_{d_i-\frac{\Delta f}{2}}^{d_i+\frac{\Delta f}{2}} |g|^2 E\{I_N(f)\}df \tag{7}$$

where g denotes the channel gain from base station to the cognitive user and Δf is the bandwidth of each subcarrier of the cognitive user.

2.3. Cognitive radio parameters

The software defined radio inside a CR provides a set of control parameters which act as input to the fitness function along with the environmental parameters. The commonly used control parameters are transmit power, modulation type, modulation index, bandwidth, channel coding rate, frame size, time division multiplexing, symbol rate, encryption, error control technique, transmission formats, etc. [50–54]. Other additional parameters such as encryption, transmission formats which change in the range of hours are not considered in this work. The environmental parameters inform the CR systems about the surrounding radio environment. The common environmental parameters used are path loss, noise power, battery life, power consumption, spectrum information, etc. These parameters help the system in deciding the mode of operation.

2.4. Fitness functions for cognitive radio

There are multiple fitness functions that need to be optimized in a wireless environment. The optimization of multiple fitness function gives rise to a set of Pareto optimal solutions. The end user has to choose a solution from this set depending on the quality of service required. Therefore the global optimization needs joint optimization of all the fitness functions. In this study, the OFDM is used for multicarrier communication system.

As mentioned in literature [24], the commonly used fitness functions in communication systems are defined below. The outputs of all fitness functions are normalized with in the range $[0, 1]$.

2.4.1. Minimization of bit error rate

This fitness function is converted to a maximization problem. For single carrier communication system, it is defined as

$$f_{min\_ber} = 1 - \frac{\log_{10}(0.5)}{\log_{10}(p_{be})} \tag{8}$$

where p_{be} is the probability of a bit error or bit error rate (BER) for a given channel and modulation scheme. This fitness function is normalized to the worst possible BER value of 0.5. For multicarrier communication systems, the corresponding fitness function $f_{mc\_min\_ber}$ is obtained by replacing p_{be} with $\overline{p_{be}}$ which represents the average BER over N subcarriers.

2.4.2. Minimization of power consumption

$$f_{min\_power} = 1 - \frac{P}{P_{max}} \tag{9}$$

where P is the transmission power of the cognitive user, P_{max} is the maximum available transmission power. For multicarrier communication systems, the corresponding fitness function $f_{mc\_min\_power}$ is obtained by replacing P with $\sum_{i=1}^{N} P_i/N$ where P_i is the power transmitted on the ith subcarrier.

2.4.3. Maximization of throughput

$$f_{max\_throughput} = \frac{\log_2 M}{\log_2 M_{max}} \tag{10}$$

where M is the used modulation index and M_{max} is the maximum available modulation index. In this case, the corresponding fitness function for multicarrier communication systems is denoted as $f_{mc\_max\_throughput}$.

In a real time scenario, there are a number of limiting factors for performance of primary as well as cognitive user networks such as power dissipation, interference, size of equipment, and rate of change of environment. For this study, two constraints are taken into account which are:

- Maximum transmissible power of the cognitive user:

$$P \leqslant P_{max} \tag{11}$$

- Maximum interference power tolerable by the primary user:

$$I(d, P) \leqslant I_{max} \tag{12}$$

where d is the spectral distance between the central frequency of the cognitive user's band and that of the primary user's band and I_{max} is the maximum interference power that can be tolerated by the primary user. The corresponding real time constraints in a multicarrier communication system can be obtained by replacing P and $I(d, P)$ by $\sum_{i=1}^{N} P_i$ and $\sum_{i=1}^{N} I_i(d_i, P_i)$ respectively where d_i is the spectral distance between the ith subcarrier in the cognitive user's band and the central frequency of the primary user's band.

2.5. BER expressions for different modulation schemes

The types of modulation included in this study are M-ary phase shift keying (PSK) and M-ary quadrature amplitude modulation (QAM). Assuming a wireless channel with additive white Gaussian noise and gray coding for bit assignment, the BER expressions for M-ary PSK and M-ary QAM are as follows:

- The BER for binary PSK (BPSK) modulation scheme is defined as

$$p_{be} = Q\left(\sqrt{\frac{P}{N}}\right) \tag{13}$$

where $Q(\cdot)$ is the Q-function representing the tail probability of the standard normal distribution, P is the signal power and N is the noise power.

- The BER for M-ary PSK modulation scheme is defined as

$$p_{be} = \frac{2}{\log_2 M} Q\left(\sqrt{2 \times \log_2 M \times \frac{P}{N}} \times \sin\frac{\pi}{M}\right) \tag{14}$$

- The BER for M-ary QAM modulation scheme is defined as

$$p_{be} = \frac{4}{\log_2 M}\left(1 - \frac{1}{\sqrt{M}}\right) Q\left(\sqrt{\frac{3 \times \log_2 M}{M-1} \frac{P}{N}}\right) \tag{15}$$

2.6. Weighted sum approach for global optimization

The optimization of multiple fitness functions independently will lead to a set of local solutions instead of a single global solution. The importance of each objective function can be represented using a quantifiable rank depending on the current scenario while optimizing multiple fitness functions. The literature [55–59] shows that there are many techniques to solve an optimization problem involving multiple fitness functions. One of these methods is weighted sum approach where each objective is provided a weight representing its importance in the current working scenario. The weighted sum approach for N objective functions is denoted as:

$$f = \sum_{i=1}^{N} w_i f_i \tag{16}$$

where f_i represents the ith objective function. w_i denotes the weight assigned to f_i while achieving the overall objective function f. w_i is subjected to the following two constraints:

$$0 \leqslant w_i \leqslant 1 \quad \text{for } i = 1, 2, \ldots, N \tag{17}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{18}$$

The advantage of using a weighted sum based approach is that the system can switch dynamically to any goal by simply changing the weight assigned to each objective.

3. Problem formulation

Based on all the discussion mentioned in previous sections, the CR engine design problem for single carrier communication system can be formulated as

$$\text{Max } f_{single} = w_1 \times f_{min\_ber} + w_2 \times f_{min\_power} + w_3 \times f_{max\_throughput} \tag{19}$$

subjected to the constraints defined by (11) and (12).

Similarly the CR engine design problem for multicarrier communication system can be formulated as

$$\text{Max } f_{multi} = w_1 \times f_{mc\_min\_ber} + w_2 \times f_{mc\_min\_power} + w_3 \times f_{mc\_max\_throughput} \tag{20}$$

subjected to the constraints discussed in Section 2.4.

The weights w_1, w_2 and w_3 provide the search direction to the optimization algorithm. The three common scenarios faced by a CR in a communication channel are shown in Table 1 [24,60]. The weights defined for each objective in a specified mode guides the optimization algorithm in evolving towards a global solution with respect to the mode. These weights also help the algorithm to change from one mode to another dynamically in a rapidly varying wireless environment.

4. Brief overview of evolutionary algorithms

In the past two decades, population based optimization algorithms have gained popularity in solving complex optimization problems. These algorithms, called bio-inspired techniques, include GA [61–63], PSO [64,65], differential evolution (DE) [66], bacterial foraging optimization (BFO) [67], ABC algorithm [68], cat swarm optimization (CSO) [69], artificial immune system (AIS) [70], etc. which also fall under the category of computational intelligence [71] or evolutionary computing [72].

Table 1
Real time scenarios for cognitive radio.

Scenario	Mode	w_1	w_2	w_3
Minimize BER	Emergency mode	0.8	0.1	0.1
Minimize power	Low power mode	0.1	0.8	0.1
Maximize throughput	Multimedia mode	0.1	0.1	0.8

4.1. Genetic algorithm

The GA is an adaptive metaheuristic search technique based on the ideas of natural selection and survival of the fittest by Darwin [73]. A random search is performed within a limited search space to solve an optimization problem. Holland was the first to propose the crossover and other recombination operators which form the building blocks of the GA [61]. He formulated a simple GA based on the process of natural adaptation. De Jong et al. [63] has shown that the GA performs well in optimizing test functions in discontinuous, noisy and multimodal search space. The GA has received wide applications in many fields of engineering such as pattern recognition and classification, bin-packing, pipeline flow control, graph coloring, structural optimization, portfolio planning, stock market prediction, aerospace engineering, and scheduling. In the GA, the population is created by randomly selecting a group of individuals known as chromosomes which are made up of a fixed number of genes. Each chromosome in the population is then evaluated using a fitness function. The individual with higher fitness has more probability of being selected for crossover operation. Two chromosomes are then selected based on their fitness to reproduce one or more offsprings. These offsprings undergo mutation operation randomly. This process continues for a certain number of generations or until a suitable solution is obtained, depending on the requirement of the end user. The GA tends to generate solutions which mostly cluster around several good solutions in the population. Due to the sorting process, the computation time of the GA increases non-linearly with the increase in the population size. The recent applications of the GA in the field of engineering includes electrical engineering [74–76], antenna design [77,78], image segmentation [79], cooperative sensing [80], vehicle routing [81], wireless communication [82], power system engineering [83], etc.

In an attempt to improve the quality of solutions, reduce the processing time and to avoid getting trapped in local optima, other EAs have been proposed by the researchers during the past two decades.

4.2. Particle swarm optimization

The PSO is a evolutionary computation technique developed by Kennedy and Eberhart [64]. It is inspired by the social behavior and motion dynamics of bird flocking or fish schooling. Unlike the GA, the basic PSO algorithm has no crossover and mutation operators. In PSO, a population of potential solutions (called particles) is created which are randomly distributed over the search space with random velocity. The position of each particle is evaluated using the fitness function. Each particle stores the best solution, it has achieved so far, as personal best. The best solution, achieved so far by the population is stored as global best. The velocity and position of each particle are updated towards its personal best and global best. The fitness of each particle's new position is evaluated using the fitness function. If the fitness of a particle's current position is better than that of its personal best position, then the personal best position is updated. The global best position is also updated which provides the final global solution to the optimization problem. Mathematically, the position and velocity of ith particle in the D-dimensional space can be defined as $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$ and $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})$ where $d(1 \leqslant d \leqslant D)$ represents the dimension. The personal best position of each particle can be represented as $P_i = (P_{i1}, P_{i2}, \ldots, P_{iD})$. The global best position of the particle swarm can be represented as $G = (G_1, G_2, \ldots, G_D)$. The update equations are:

$$V_{id} = w * V_{id} + c * r_1 * (P_{id} - X_{id}) + c * r_2 * (G_d - X_{id}) \tag{21}$$

$$X_{id} = X_{id} + V_{id} \tag{22}$$

where w is the inertia weight, c is the acceleration constant and r_1 and r_2 are two random numbers uniformly distributed in the range $[0, 1]$.

In past decade, the PSO has found successful applications in many fields. It is also demonstrated in literature that the PSO performs better and need less computation time compared to the GA. The less number of parameters to adjust in the PSO algorithm makes it more popular. The PSO does not involve sorting of fitness values of solutions in any process, which is a significant computational advantage over the GA, especially when the population size is large. The updates of velocity and position in the PSO only require a simple arithmetic operation of real numbers. Since the PSO uses the floating point arithmetic, the density of the solutions within the solution space are much higher than that of the GA. A large number of variants of the PSO algorithm have been proposed in literature to improve its performance. The recent applications of the PSO are in the field of antenna engineering [84], power electronics [85], radar engineering [86], image processing [87], electrical engineering [88,89], etc.

4.3. Differential evolution

The DE is a stochastic, population based optimization algorithm developed by Storn and Price [66]. The key difference between the DE and the GA/PSO is in the mechanism for generating new solutions. The DE, in comparison to GA/PSO, generates a new solution by combining several solutions with the candidate solution. The population in the DE evolves through repeated cycles of mutation, crossover, and selection which are different than the ones used in the GA. In the DE, a potential solution is represented using a parameter vector of real numbers whose initial parameters are randomly selected from the search space. Each parameter vector undergoes mutation, recombination and selection process. For every parameter vector (called target vector), three distinct parameter vectors are randomly selected from the population. A new parameter vector (called donor vector) is generated by adding the weighted difference of two parameter vectors to the third parameter vector. Assuming the ith parameter/target vector in the D-dimensional space as $X_i = (X_{i,1}, X_{i,2}, \ldots, X_{i,D})$, the donor vector in nth generation is obtained as

$$V_{i,d}(n+1) = X_{r_1,d}(n) + F * (X_{r_2,d} - X_{r_3,d}) \tag{23}$$

r_1, r_2 and r_3 are random mutually different integers in the range $[0, N]$ where N is the population size. F is a real and constant factor in the range $[0, 2]$. A trial vector $Y_{i,d}(n+1)$ is generated from the elements of the target vector and the elements of the donor vector based on certain probability. The trial vector $Y_{i,d}(n+1)$ is compared with the target vector $X_{i,d}(n)$ and the one with the best fitness is admitted to the next generation of the DE as $X_{i,d}(n+1)$. These processes of mutation, recombination and selection continue until some stopping criterion is reached. The popularity of the DE increased at a vast rate due to easy methods of implementation and negligible parameter tuning. A large number of variants of the DE algorithm have been developed in order to improve the performance of the algorithm in optimizing complex problems. The exploration ability of the DE is comparable to the PSO while the diversification is better as the best solution in the population does not influence the other solutions. The DE has recently got wide applications in the field of electromagnetics [90–92], electrical engineering [93,94], graph theory [95], etc.

4.4. Bacterial foraging optimization

The BFO is a nature inspired optimization algorithm proposed by Passino [67]. It is based on the foraging strategy of the *Escherichia Coli* bacterium cell. In the BFO, a potential solution of an optimization problem is represented using the coordinates of a bacterium. Each bacterium follows the foraging dynamics of the population and converges towards the optimal solution. A chemotaxis process is carried out where the bacterium swims for a period of time in the same direction or it may tumble depending on the fitness of the bacterium. Assuming the position of the ith bacterium as θ^i, the new position is defined as

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{24}$$

j, k, l are indices corresponding to chemotaxis, reproduction and elimination-dispersal processes. $\Delta(i)$ is a random number in the range $[-1, 1]$ and $C(i)$ denotes the step size. The population also undergoes a process of swarming where individuals aggregate into groups and thus move as concentric patterns of swarms with high bacterial density. After completion of swarming process, half of the population having best fitness undergoes reproduction, eliminating the other half of the population. An elimination and dispersal process is carried out which does not allow the bacteria to fall into local optima. In this process, some bacteria are removed from the population at random with a very small probability. The new bacteria are placed at random locations in the search space. Experiments with different complex and multimodal benchmark functions reveal that the BFO possesses a poor convergence behavior, and its performance heavily degrades with the increase in dimensionality of search space and the problem complexity. Several BFO variants have been proposed in literature to improve its optimization performance. The BFO has been successfully applied in many applications such as transmission loss reduction [96], control engineering [97], harmonic estimation [98], machine learning [99], antenna parameter calculation [100], and power system engineering [101–103].

4.5. Artificial bee colony

The ABC is a newly developed metaheuristic algorithm, proposed by Karaboga [68], based on the foraging behavior of honey bees. In the ABC algorithm, the position of a food source represents a possible solution of an optimization problem and the nectar amount of the food source represents the fitness of the solution. Initially the population is randomly distributed in the search space and the control parameters of the ABC algorithm are also initialized. The nectar amount of the initial food sources are evaluated. The population consists of the employed, onlooker, and scout bees. Each employed bee finds out a new food source and evaluates its nectar amount. Let x_i be the position of the ith food source and F_i represents the nectar amount of ith food source. The new food source is obtained by

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{25}$$

where k is a randomly chosen index for food source in the neighborhood of i and j is a randomly chosen dimension from the set $\{1, 2, \ldots, D\}$ where D is the total number of dimensions for a food source. ϕ_{ij} is a random number in the range $[-1, 1]$. If the nectar amount of the new food source is more than that of the previous source, the employed bee memorizes the new food source position.

The employed bees share the information about the nectar amount of food sources with the onlooker bees. The onlooker bees select the food source depending on the nectar amount of the food source, i.e. F_i. Food source with higher nectar amount has more probability of getting selected by the onlooker bees. The probability value associated with a food source is determined by

$$P_i = \frac{F_i}{\sum_{j=1}^{N_s} F_j} \tag{26}$$

where N_s is the number of food sources. The onlooker bee finds new food source and evaluates its nectar amount. If the nectar amount of the new food source is higher than that of the previous one, then it memorizes the new food source. If the nectar amount of a food source does not improve in a fixed number of trials, then the food source is abandoned and the corresponding employer bee becomes a scout bee. These abandoned food sources are replaced by new random food sources for scouts. These steps are repeated until the stopping criteria is met. Karaboga and Basturk have studied the performance of the ABC algorithm on unconstrained and constrained optimization problems [104–107]. Karaboga et al. have also used the ABC algorithm for training the neural network [108,109]. The ABC algorithm is robust and has fewer control parameters, fast convergence and high flexibility. The ABC algorithm can be used for solving both multidimensional and multimodal optimization problems. Although the ABC is a recently developed algorithm, still it has found successful applications in the field of wireless communication [110,111], electrical engineering [112,113], image processing [114], routing [115], etc.

4.6. Cat swarm optimization

The CSO is a new algorithm of swarm intelligence proposed by Chu et al. [69] and is inspired by the natural behavior of cats. Cats have a strong curiosity towards moving objects and possess good hunting skill. Even though cats spend most of their time in resting, they always remain alert and move very slowly. When the presence of a prey is sensed, they chase it very quickly spending large amount of energy. These two characteristics of resting with slow movement and chasing with high speed are represented as seeking and tracing modes respectively. In the CSO algorithm, these two modes have been mathematically modeled for solving complex optimization problems.

The CSO algorithm reaches its optimal solution using two groups of cats, i.e. one group containing cats in seeking mode and other group containing cats in tracing mode. The two groups combine to solve the optimization problem. A mixture ratio (MR) is used which defines the ratio of the number of cats in the tracing mode to that of the number of cats in the seeking mode. The positions and velocities of cats in D-dimensional space are randomly initialized. According to MR, cats are randomly picked from the population and their flag is set to the seeking mode, and for others the flag is set to the tracing mode. The fitness of each cat is evaluated and the position of the cat with best fitness is stored. If the cat is in seeking mode, the cat undergoes the seeking mode process, otherwise it undergoes the tracing mode process. Further, the cats are again randomly picked from the population according to MR and their flag is set to seeking mode, and for others the flag is set to tracing mode. The termination condition is checked, if satisfied, the program is terminated. Otherwise the steps are repeated. The seeking mode corresponds to a global search technique in the search space of the optimization problem. Some of the terms related to this mode are: seeking memory pool (SMP) represents the number of copies of a cat produced in the seeking mode; seeking range of selected dimension (SRD) represents the maximum possible change in the position of a cat; counts of dimension to change (CDC) represents the number of dimensions to be mutated; self position consideration (SPC) decides if the current position of the cat can have the chance to be retained in this generation. The SPC is a predefined flag with the value "true" or "false". If SPC="false", T copies of ith cat are created, i.e. $U_j = X_i$ where $j = 1, 2, \ldots, T$. Otherwise $T - 1$ copies of ith cat are created because the original i^{th} cat will take one place in the candidates. Based on CDC, the position of each copy is updated by randomly adding or subtracting SRD percents the present position value.

$$U_{jd} = U_{jd} * (1 + k * SRD) \tag{27}$$

where d represents the selected dimension and k is a random binary number, i.e. $[-1, 1]$. Further, the fitness of all copies are evaluated and the best candidate is stored as U_{best}. The ith cat is replaced with the best candidate U_{best}, i.e. $X_i = U_{best}$. In tracing mode, the rapid chase of the cat is mathematically modeled as a large change in its position. The velocity of the cat in this mode is updated using (21) excluding the second component in the summation.

Similarly the position of the cat is updated using (22). The advantage of the CSO lies in the parallel implementation of global exploration and local exploitation. In certain cases, this might lead to higher computation time than the PSO but less than the GA and ABC. Recently the CSO has been successfully applied in clustering [116,117], feature selection [118], image processing [119], etc.

Although a large number of EAs are proposed in literature, their application to real world optimization problems are limited in number. Several variants of each EA are also proposed in last few years to provide improved performance. It is already discussed in Section 1 that the binary GA, its variants and the discrete binary PSO have already been used in the CR engine design. But most of these algorithms have used binary representation for control parameters of the CR. It is also reported in literature that the recently proposed EAs perform better than the GA and PSO. Since the performance of an EA depends on the nature of optimization problem and its environment, this paper provides a generalized approach for EA based CR engine design. A set of EAs are used in this investigation which includes the GA, PSO, CSO, BFO, ABC, and DE. The results corresponding to these six algorithms provide a overall picture of the optimization problem and its possible solution obtained using EAs.

5. Performance metrics

With the existence of different EAs, it is necessary to quantify the performance of each algorithm. The important goal in an optimization algorithm is to discover the optimal fitness in the least possible number of generations, computation time and fitness function evaluations. Although these are mostly related to each other, but in certain cases these goals are somewhat conflicting in nature. Hence, a single metric cannot decide the performance of an algorithm in an absolute sense. Based on these discussions, we use four performance metrics commonly used in literature.

5.1. Optimal fitness

This metric, measures the quality of solution provided by an EA. In this study, the weighted sum approach is used in each EA for optimizing multiple normalized fitness functions. Hence, as the optimal fitness approaches unity, the quality of solution improves further.

5.2. Optimal generation

It refers to the generation where the optimal fitness is found by each algorithm. This gives a brief idea about the convergence rate of the EA. In certain cases, the algorithm starts with a very good global search but takes more time at the end of the search to reach its optimal fitness due to poor local search around the global optima. In these cases, this metric might not provide the exact knowledge of the convergence rate.

5.3. Optimal computation time

This metric deals with the amount of processing time needed by each algorithm in order to reach their optimal fitness. It also denotes the processing time needed to reach its optimal generation. Although this metric is related to the optimal generation metric, it also provides knowledge about the computational complexity of each algorithm. The standard deviation of this metric reveals the consistency in the processing time requirement of each algorithm.

5.4. Optimal fitness function evaluations

In the conventional EAs such as classical GA and PSO, the number of fitness function evaluations is the product of the size of population and the number of generations. But this concept does not work in the recently developed EAs due to the involvement of different processes in each generation. In some cases, each candidate solution evaluates the fitness function more than once in one generation. Hence, it is possible for an EA to reach the optimal fitness much earlier than others due to large number of fitness evaluations in each generation. Thus, this metric also plays an important role in evaluating the performance of an EA.

6. Simulation result and analysis

The CR models shown in Figs. 1 and 2 are considered in this investigation. The bandwidth of primary user as well as secondary user is 5 MHz. The intermediate frequency of the primary user is 650 MHz. A Rayleigh fading channel with additive Gaussian noise is considered whose mean value is 1 and the PSD is 10^{-8} W/Hz. The maximum transmissible power of the cognitive user is 5 W and the maximum interference power tolerable by the primary user is 10 mW. The modulation schemes considered in this study are listed in Table 2 with their corresponding encoded values.

Simulation study is carried out in MATLAB to demonstrate the performance of different EAs in designing a CR engine. The results are compared in terms of fitness convergence characteristic, optimal fitness, computation time and number of fitness evaluations. The initial population chosen for all the EAs is 50. After several experiments with different simulation parameters for each algorithm, the following combination of parameters are found to be providing the best performance.

Table 2
Modulation schemes for simulation study.

Modulation	Encoded Value
No modulation	0
BPSK	1
QPSK	2
8 QAM	3
16 QAM	4
32 QAM	5
64 QAM	6
128 QAM	7

- **GA:** single point crossover with probability 0.8, probability of mutation is 0.1 and number of bits per variable are 10.
- **PSO:** inertia weight is linearly decreased from 0.9 to 0.4, both the acceleration constants are taken as 2.
- **DE:** scaling factor is 2 and crossover probability is 0.8.
- **BFO:** probability of elimination and disposal is 0.25, maximum swimming length is 3, number of chemotactic loops is 2, number of reproduction loops is 5, and number of elimination and dispersal loops is 10.
- **ABC:** food limit is 100, number of onlooker bees is 25, number of employed bees is 25, and number of scouts is 1.
- **CSO:** size of seeking memory pool is 5, seeking range of selected dimension is 20%, counts of dimension to change is 80%, mixture ratio is 0.9, acceleration constant is 2, and inertia weight is linearly decreased from 0.9 to 0.4.

6.1. Single carrier communication system

The performance of different algorithms in single carrier communication system is investigated in this sub-section. The CR scenario shown in Fig. 3 is considered. For this study, the number of generations is set to 100. Different results obtained with each algorithm are analyzed, depending on the mode of operation listed in Table 1. In each case, the results obtained from 30 independent experiments are reported.

6.1.1. Emergency mode of operation

Fig. 4 shows the fitness convergence characteristics obtained with different algorithms in emergency mode of operation in the CR. It is observed that the convergence rate of all algorithms are almost similar in emergency mode for a single carrier communication system. The six EAs are able to converge to the optimal fitness with in 20 generations.

Table 3 shows the optimal generation in which each algorithm reaches the optimal fitness value. The values of optimal fitness indicate that the six algorithms perform similarly in the emergency mode of operation for a single carrier communication system. The standard deviation for optimal fitness shows the consistency in the performance of each algorithm. However, when compared, the DE algorithm takes the highest number of generations to reach the optimal fitness. The computation time required to reach the optimal generation is also shown in Table 3 along with the number of fitness function evaluations carried out by each algorithm. The GA requires the highest computation time of 48 ms. The inherent feature of the GA, i.e. binary to decimal conversion and vice versa contributes to high computation time. The CSO requires only 0.1 ms to reach its optimal fitness. The BFO carries out the highest number of fitness function evaluations in order to reach its optimal fitness.

The high rate of convergence and low computation time in emergency mode facilitates the use of EAs in time variant wireless environment.

6.1.2. Low power mode of operation

Fig. 5 shows the fitness convergence characteristics obtained with different algorithms for low power mode of operation in the CR. In this mode, the rate of convergence of each algorithm is slower than their corresponding rate in emergency mode of operation shown in Fig. 4. It is also seen that the steady state value achieved in this mode is less than that achieved in emergency mode. This result is also verified by the values of optimal fitness shown in Table 4.

Table 4 reveals that, except the BFO, the other five algorithms perform approximately similar with respect to optimal fitness with very low values of standard deviation. The algorithms need more number of generations for local search near the global optima. Table 4 also shows the computation time required to reach the optimal generation. In this mode of operation, the PSO needs the highest computation time of 922 ms to reach its optimal fitness. Table 4 also shows that similar to emergency mode, the BFO carries out the highest number of fitness function evaluations in this mode to reach its optimal fitness.

6.1.3. Multimedia mode of operation

The fitness convergence characteristics in Fig. 6 shows that the rate of convergence of the six algorithms is high in multimedia mode of operation. It can be seen that the

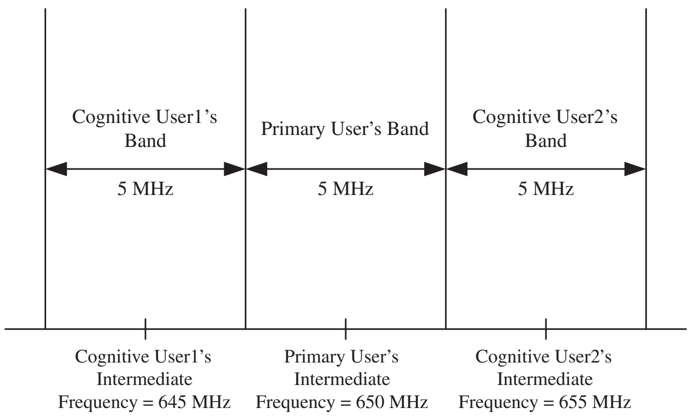

Fig. 3. Co-existence scenario of primary and cognitive users in single carrier communication system undertaken for simulation study.

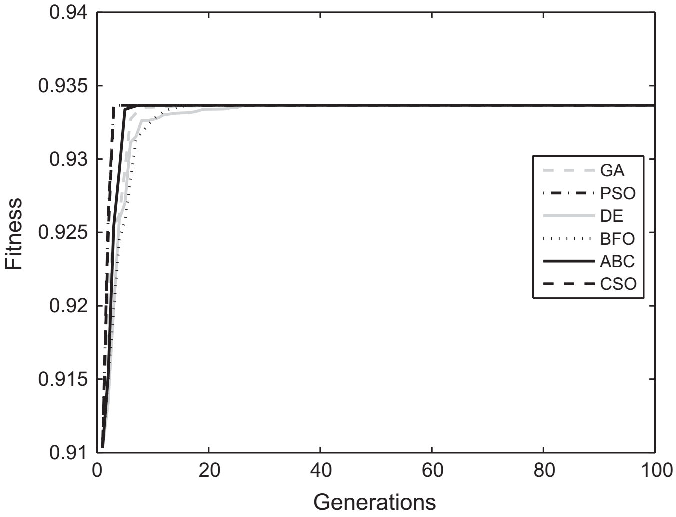

Fig. 4. Fitness convergence characteristics in emergency mode of operation in single carrier communication system.

Table 3
Optimal fitness obtained and corresponding optimal generation, optimal computation time (in s) and optimal fitness function evaluation required by different algorithms in emergency mode of operation in single carrier communication system.

Algorithm	Fitness		Generation		Comp. Time		Function evaluations
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	
GA	0.9237	0.0000[a]	19	4	0.0488	0.0371	950
PSO	0.9237	0.0000[a]	3	1	0.0030	0.0008	150
DE	0.9235	0.0000[a]	32	3	0.0133	0.0078	3200
BFO	0.9237	0.0000[a]	17	4	0.0050	0.0030	4250
ABC	0.9237	0.0000[a]	8	2	0.0005	0.0003	406
CSO	0.9237	0.0000[a]	3	1	0.0001	0.0000	210

[a] Values less than 10^{-4} have been displayed as 0.0000.

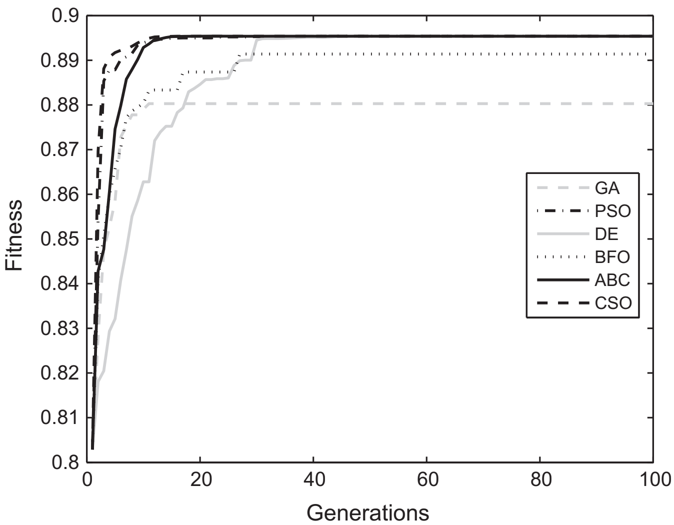

Fig. 5. Fitness convergence characteristics in low power mode of operation in single carrier communication system.

algorithms converge at a very high rate to a value of 0.9043.

The values of optimal fitness in Table 5 testify the convergence of each algorithm. Although the six algorithms

Table 4
Optimal fitness obtained and corresponding optimal generation, optimal computation time (in s) and optimal fitness function evaluation required by different algorithms in low power mode of operation in single carrier communication system.

Algorithm	Fitness		Generation		Comp. Time		Function evaluations
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	
GA	0.8803	0.0000[a]	11	3	0.0299	0.0151	550
PSO	0.8954	0.0000[a]	42	3	0.9224	0.0567	2100
DE	0.8951	0.0000[a]	44	4	0.0270	0.0080	4400
BFO	0.8271	0.0166	28	4	0.0329	0.0153	7000
ABC	0.8954	0.0000[a]	17	6	0.0082	0.0019	862
CSO	0.8954	0.0000[a]	16	4	0.0089	0.0008	1120

[a] Values less than 10^{-4} have been displayed as 0.0000.

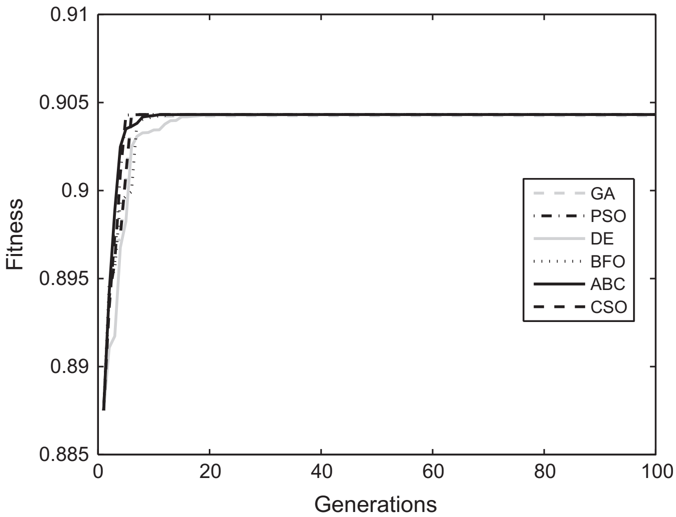

Fig. 6. Fitness convergence characteristics in multimedia mode of operation in single carrier communication system.

perform similarly with respect to optimal fitness, the optimal generation required for each algorithm vary significantly. Similar to low power mode, the DE needs the highest number of generations to reach its optimal fitness in this mode. The computation time requirement along with the optimal number of fitness evaluations are listed in Table 5. In this mode, the PSO needs the highest computation time but the least number of fitness function evaluations to reach its optimal fitness.

The single carrier communication system involves only one carrier with two optimization parameters. Since the dimensionality of the problem is low, there are few possibilities of algorithms getting trapped in local optima. Due to the low complexity of the optimization problem, the EAs are able to optimize the parameters quickly to reach the global optima. Therefore, the performances of the six algorithms in single carrier communication system are similar with respect to the optimal fitness, but limited in terms of memory requirement and computation time. Looking at the performance of the six algorithms, the ABC can be considered as the best choice for any mode of operation in single carrier communication system. How-

Table 5
Optimal fitness obtained and corresponding optimal generation, optimal computation time (in s) and optimal fitness function evaluation required by different algorithms in multimedia mode of operation in single carrier communication system.

Algorithm	Fitness		Generation		Comp. time		Function evaluations
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	
GA	0.9042	0.0000[a]	8	2	0.0313	0.0308	400
PSO	0.9043	0.0000[a]	5	3	0.1161	0.0075	250
DE	0.9043	0.0000[a]	19	3	0.0119	0.0048	1900
BFO	0.9043	0.0000[a]	12	2	0.0128	0.0061	3000
ABC	0.9043	0.0000[a]	10	4	0.0049	0.0027	507
CSO	0.9043	0.0000[a]	6	3	0.0032	0.0002	420

[a] Values less than 10^{-4} have been displayed as 0.0000.

ever, the selection of an algorithm for any application depends on the amount of resources available such as hardware memory and processor speed.

With the introduction of multicarrier communication systems, the use of single carrier systems are limited to few applications. In this study, the advantage of multicarrier communication systems over single carrier communication systems can be realized using the simulation results.

6.2. Multicarrier communication system

In this part of study, the performances of the six algorithms in different modes of operation are investigated in presence of a multicarrier communication system. The overall fitness function in multicarrier communication system is very sensitive to fitness of individual subcarrier. Hence, each subcarrier must be optimized independently to adapt to the varying environment. The CR scenario shown in Fig. 7 is considered where each sideband of 5 MHz is divided into 16 subbands, each occupied by a subcarrier of the OFDM system. The symbol duration for the OFDM system is 100 µs. Different results obtained with each algorithm, depending on the mode of operation listed in Table 1, are analyzed in detail. In each case, the results obtained from 30 independent experiments are reported. The number of generations in this part of study is set to 2000.

6.2.1. Emergency mode of operation

The fitness convergence characteristics of different algorithms in emergency mode of operation are shown in Fig. 8. The ABC algorithm performs better than the other five algorithms in terms of optimal fitness, but the rate of convergence is low. There is significant difference between the optimal fitness achieved by each algorithm and their convergence speed. Table 6 shows that the recently developed EAs perform much better than the GA with respect to optimal fitness. The CSO needs the least number of generations, i.e. 748 to reach its optimal fitness of 0.8549 and hence needs the least computation time.

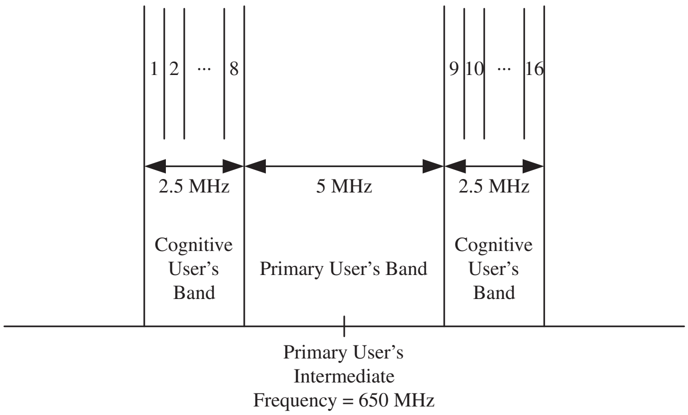

Fig. 7. Co-existence scenario of primary and cognitive users in multicarrier communication system undertaken for simulation study.

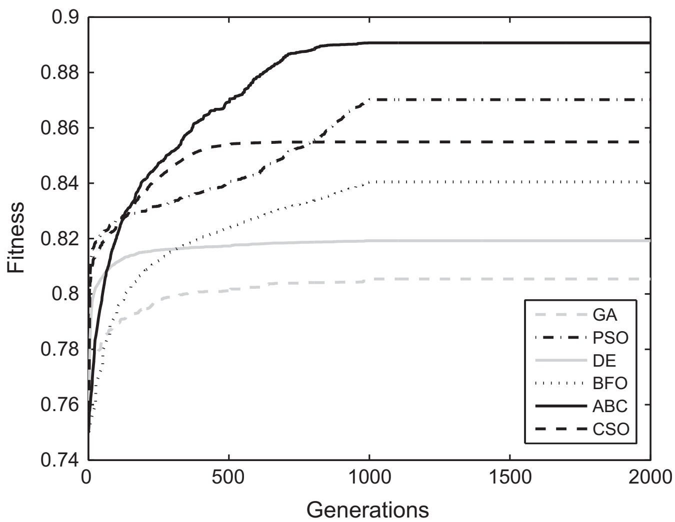

Fig. 8. Fitness convergence characteristics in emergency mode of operation in multicarrier communication system.

Table 6
Optimal fitness obtained and corresponding optimal generation, optimal computation time (in s) and optimal fitness function evaluation required by different algorithms in emergency mode of operation in multicarrier communication system.

Algorithm	Fitness		Generation		Comp. time		Function evaluations
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	
GA	0.8054	0.0062	997	27	17.4231	0.1142	49,850
PSO	0.8702	0.0139	1001	18	13.4947	0.6926	50,050
DE	0.8192	0.0019	983	6	2.4228	0.0113	98,300
BFO	0.8405	0.0185	1001	15	1.3410	0.0898	250,250
ABC	0.8907	0.0014	996	14	3.9943	0.0226	50,094
CSO	0.8549	0.0116	748	12	0.5163	0.0128	52,360

6.2.2. Low power mode of operation

Fig. 9 shows the fitness convergence characteristics of different algorithms in low power mode of operation in multicarrier communication system. The CSO algorithm performs better than the other five algorithms in terms of optimal fitness and rate of convergence. The DE algorithm falls into local optima prematurely. The CSO needs 541 number of generations to reach its optimal fitness of 0.9088. Table 7 reveals that the CSO needs the least computation time to reach its optimal fitness with the least number of fitness evaluations.

6.2.3. Multimedia mode of operation

The fitness convergence characteristics of different algorithms in multimedia mode of operation is shown in Fig. 10. Except the DE and ABC, the other four algorithms perform approximately similar in terms of optimal fitness. The DE and ABC fall into local optima prematurely. The GA and CSO have very good convergence rates. But due to poor local search around local optima, the GA takes 975 generations to reach optimal fitness whereas the CSO needs only 351 generations as shown in Table 8. The CSO also needs the least computation time to reach its optimal fitness with 24,570 number of fitness function evaluations.

The aforementioned multicarrier communication system involves optimization of 32 parameters accounted for 16 subcarriers with each characterized by two parameters. This makes the optimization problem a multidimensional and multimodal problem. The EAs are more likely to get trapped in local optima. Therefore, the performances

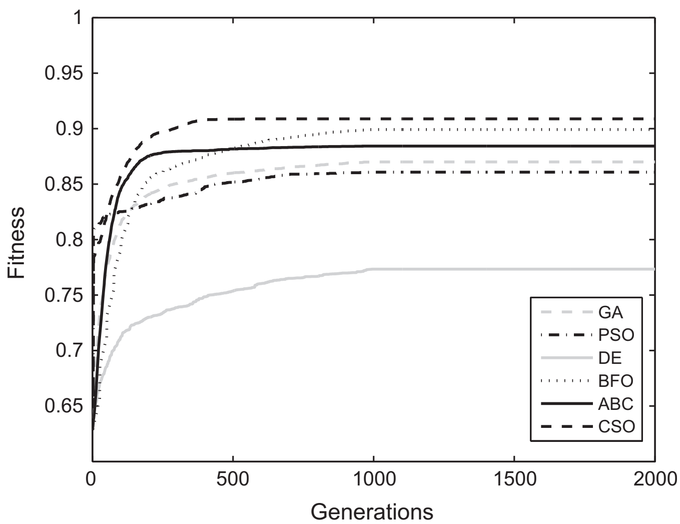

Fig. 9. Fitness convergence characteristics in low power mode of operation in multicarrier communication system.

Table 7
Optimal fitness obtained and corresponding optimal generation, optimal computation time (in s) and optimal fitness function evaluation required by different algorithms in low power mode of operation in multicarrier communication system.

Algorithm	Fitness		Generation		Comp. time		Function evaluations
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	
GA	0.8700	0.0035	1001	17	14.6113	1.5596	50,050
PSO	0.8607	0.0068	995	18	9.4858	2.4862	49,750
DE	0.7734	0.0126	998	15	2.2847	0.1579	99,800
BFO	0.8991	0.0100	977	12	1.3371	0.0925	244,250
ABC	0.8843	0.0018	969	22	3.0523	0.8787	48,736
CSO	0.9088	0.0031	541	16	0.3237	0.0278	37,870

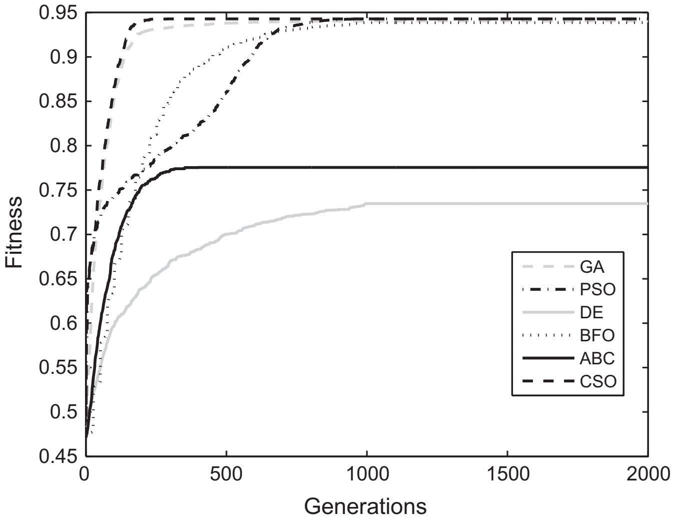

Fig. 10. Fitness convergence characteristics in multimedia mode of operation in multicarrier communication system.

Table 8
Optimal fitness obtained and corresponding optimal generation, optimal computation time (in s) and optimal fitness function evaluation required by different algorithms in multimedia mode of operation in multicarrier communication system.

Algorithm	Fitness		Generation		Comp. time		Function evaluations
	Avg.	S.D.	Avg.	S.D.	Avg.	S.D.	
GA	0.9406	0.0005	975	11	11.5075	0.0464	48,750
PSO	0.9427	0.0002	969	18	11.0436	0.0685	48,450
DE	0.7347	0.0272	995	23	2.0479	0.0181	99,500
BFO	0.9386	0.0093	997	24	0.9731	0.0054	249,250
ABC	0.7755	0.0433	401	26	1.1646	0.0037	20,168
CSO	0.9428	0.0000[a]	351	17	0.1853	0.0009	24,570

[a] Values less than 10^{-4} have been displayed as 0.0000.

of the six algorithms in multicarrier communication system vary significantly with respect to all metrics. It is seen that in most cases, the CSO provided the best average results for different performance metrics, and hence will be a reasonable choice for any mode of operation in multicarrier communication system. Practically once the designer decides the target performance in terms of fitness functions, an algorithm can be selected depending on the trade-off between accuracy and computation time while looking at the hardware memory, processor speed, etc.

7. Conclusion

In this paper, a CR engine is designed based on the recently developed EAs. A weighted sum approach is used for optimizing multiple objectives in a wireless environment. The evolutionary algorithms used in this study are GA, PSO, DE, BFO, ABC, and CSO. The spectral interference between the primary user and the cognitive user has been considered to imitate the practical scenario in wireless communication. Due to limitations on the size and performance of a CR, constraints have been put on transmission power of the cognitive user and interference power tolerable by the primary user. The CR engine designs for single and multicarrier communication systems have been dealt separately. The simulation results provide an extensive knowledge on the performance of EAs in adapting the parameters of a CR. The performance assessment of different algorithms is carried out using four metrics. The average and standard deviation values of different metrics show that the CSO is a reasonable choice for CR engine design.

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