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Article

Optimization of Cognitive Radio System Using Self-Learning Salp Swarm Algorithm

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Abstract: Cognitive Radio (CR) has been developed as an enabling technology that allows the unused or underused spectrum to be used dynamically to increase spectral efficiency. To improve the overall performance of the CR system it is extremely important to adapt or reconfigure the system parameters. The Decision Engine is a major module in the CR-based system that not only includes radio monitoring and cognition functions but also responsible for parameter adaptation. As meta-heuristic algorithms offer numerous advantages compared to traditional mathematical approaches, the performance of these algorithms is investigated in order to design an efficient CR system that is able to adapt the transmitting parameters to effectively reduce power consumption, bit error rate and adjacent interference of the channel, while maximized secondary user throughput. Self-Learning Salp Swarm Algorithm (SLSSA) is a recent meta-heuristic algorithm that is the enhanced version of SSA inspired by the swarming behavior of salps. In this work, the parametric adaption of CR system is performed by SLSSA and the simulation results show that SLSSA has high accuracy, stability and outperforms other competitive algorithms for maximizing the throughput of secondary users. The results obtained with SLSSA are also shown to be extremely satisfactory and need fewer iterations to converge compared to the competitive methods.

Keywords: Cognitive radio; meta-heuristic algorithm; cognitive decision engine; salp swarm algorithm

1 Introduction to Cognitive Radio Technology

The exponential growth of wireless communication technology-based applications has resulted in an increase in spectrum demand. However, the major impediment to meeting this demand is a lack of radio resources. The Federal Communications Commission's (FCC) research has established that the primary cause of this shortage is licensed users' spatial or temporal underutilization of the spectrum [1]. In frequencies below 3 GHz, non-line-of-sight radio propagation is preferred, and spectrum utilization efficiency varies between 15%–85% in these bands [2]. The current spectrum allocation strategy is rigid, assigning a specific band to each licensed or primary user (PU), which has resulted in spectrum underutilization [3].

Cognitive radio (CR) technology has garnered much interest in recent years as a means of alleviating the seeming scarcity of accessible bandwidth. Motivated by FCC research indicating inefficient use of a significant portion of the licensed spectrum, Joseph Mitola proposed the concept of CR [4]. This technique enables unlicensed users to dynamically search for and operate in underutilized spectrum bands, therefore boosting spectral efficiency without interfering with PUs [5,6].

CR is defined as an intelligent system that can modify and reconfigure itself in response to its surroundings in order to satisfy the end user's expectations. Cognition and reconfiguration are critical capabilities that contribute to the CR's intelligence [7]. These capabilities are detailed below:

Cognitive capability It offers spectrum awareness in terms of spectral occupancy, channel conditions, and so on, and accomplishes this by recording the spatial and temporal changes occurring in the environment while avoiding interfering with other users. When the radio performs the specific responsibilities [8], the full cognitive cycle is completed: (i) Spectrum sensing identifies the frequency bands that are open for opportunistic use. (ii) Spectrum management determines the optimal channel configuration based on the end user's requirements. (iii) Spectrum sharing enables impartial spectrum scheduling by concurrent CR users to coordinate access to a specified channel. (iv) Spectrum mobility refers to the process of leaving a channel when the principal user becomes active and seamlessly transitioning to another unused channel.

Re-configurability It permits dynamic programming of the device by altering the operational settings on the fly without requiring any changes to the hardware components. The CR device may be set to transmit and receive on a variety of different frequencies, and its hardware architecture supports a variety of transmission access methods. Operating frequency, transmission power, modulation technique, and channel coding are just a few of the characteristics that may be customized based on user requirements, current environmental variables, and prior experiences [9]. The cognitive decision engine (CDE) is the module that combines the qualities of observation, cognition, and reconfiguration [10].

CDE is a critical component of CR since it enables the radio to adapt intelligently to its operational environment. After receiving input from the environment/user (observation), CR evaluates and classifies the situation in order to identify an appropriate response to the stimulus (cognition) and makes the decision (re-configuration). The components that contribute to cognitive capability development and CR functioning are described below [11]:

Sensors The spectrum sensing module is made up of radio frequency (RF) sensors and internal state sensors. RF sensors detect the radio environment and channel parameters such as path loss, noise power, and interference power. Internal status sensors, on the other hand, are responsible for recording information about the user's present service requirements and the radio's battery level.

Policy engine Policies are government-defined regulations that constraint CR's activities and must be considered while making choices. The policy engine guarantees that the optimization process produces transmission parameters that conform with local regulatory standards.

Decision module The CDE's decision-making component analyzes sensor data and then determines the necessary actions. If optimization is necessary, the decision module supplies the optimizer with the optimization objectives (e.g., high throughput or low power consumption). Additionally, it establishes a time limit and stopping conditions for achieving these objectives.

Optimizer An optimizer provides the set of transmission parameters optimal for given environmental conditions and user-oriented information to attain extreme performance.

Thus, the decision-making module integrates sensor data and makes an autonomous choice based on the current environmental condition. The choice is made using reconfigurable parameters that are transmitted to the radio, which is implemented as a software-defined radio (SDR). Following that, SDR modifies its settings in accordance with the decision module's decisions.

Radio parameters for CDE are classified into environmental and transmission parameters [12,13] as described below:

Input or environmental parameters These are the radio characteristics that are sent to the CR via RF sensors that include path loss, signal-to-noise ratio (SNR), noise power, and channel attenuation. Internal state sensors provide information on the radio's battery level and the type of service requested by the user. This information also serves as an input parameter.

Output or transmission parameters Transmission parameters serve as reconfigurable or tunable CR parameters, which are created by the decision module in order to meet the user's QoS requirements in the current operating environment. Transmission characteristics include transmit power, bandwidth, modulation level, symbol rate, time division duplex percentage, and the size of a transmission frame in bytes.

Due to the fact that the input variables are dependent on environmental conditions and user needs, these are treated as static in the current situation. As a result, transmission parameters, also known as decision variables, must be adjusted to meet the end user's defined objectives and QoS parameters. The particular aim might be to minimize bit error rate (BER), to maximize throughput, to minimize power consumption, and/or to minimize interference. The optimal set of transmission parameters can be obtained using various available techniques such as Case-based system (CBS) [14,15], Rule-based system (RBS) [16], Artificial neural networks (ANN) [17], Machine learning (ML) [18] and meta-heuristic algorithms.

Because of its cognitive nature, the CR may interact with the environment in real time, this interaction helps to identify the optimal communication parameters to be adapted to the changing radio environment. In other words, CR examines environmental information and identifies the optimum possible set of transmission parameters to meet certain service performance objectives. By defining the environmental inputs, the correctness of the CR system choices is substantially affected. The definition of the collection of CR controlled transmission parameters also influences radio efficiency considerably. Meta-heuristic strategies have been employed successfully in the literature over the last two decades to resolve the parameter problem of CDE adaptation.

There is no one algorithm among meta-heuristics, according to the No Free Lunch (NFL) theorem, which finds the best solution for all sorts of optimization tasks. When applied to some other set of problems, an algorithm which exhibits good results on one problem can demonstrate poor performance. Therefore, it is an open field of research that searches enhanced, novel or hybrid optimization methods and their use in various fields. In order to propose new meta-heuristic procedures and improve the capability of current techniques, substantial study was carried out in this area.

The performance of recently introduced meta-heuristic methods for parameter reconfiguration in CR-based systems is explored in this paper. There are five alternative transmission scenarios to consider, each with its own set of user requirements and radio battery level. Determining the appropriate value of transmission parameters is a difficult issue for a with high dimensional multi-carrier system. However, meta-heuristic optimization approaches provide a quick and easy solution to the abovesaid issue. The performance of the self-learning salp swarm algorithm (SLSSA) [19] has been investigated in this study, and an optimal solution for each transmission situation is presented. SLSSA have a few algorithm-specific parameters and can find an optimal solution without much control-parameter-setting, and minimizing the algorithm's complexity.

The structure of the paper is as follows: Related work based on meta-heuristic algorithms to solve the parameter adaptation problem for CDE is given in Section 2. Section 3 describes self-learning salp swarm algorithm (SLSSA) in detail. Transmission Parameters Optimization of CR System using SLSSA is detailed in Section 4. Simulation outcomes are given in Section 5 and Section 6 concludes the paper with possible future directions.

2 Related Work

Meta-heuristic algorithms are easy to operate, have high convergence speed and are able to tackle optimization problems that are non-linear, non-convex, highly complex and/or multi-dimensional [20]. The process of optimization utilizing meta-heuristic algorithms begins with the random solutions generation. Then these initial solutions are altered over a certain number of iterations. The mechanisms involved in updating or altering the solutions differentiate those algorithms. Meta-heuristic techniques have been popular among researchers and scholars in the recent two decades. The problem of parameter adjustments for CDE were successfully applied in the literature. Metaheuristic algorithms that have been employed for optimizing the CDE design include: Genetic algorithm [21], Particle swarm optimization (PSO) [22], Artificial bee colony (ABC) algorithm [23], Ant colony optimization (ACO) [24], Simulated annealing (SA) [25], Biogeography based optimization (BBO) [26], Cat swarm optimization (CSO) [13]. This work focuses on meta-heuristic techniques to resolve the problem of parameter adaptation in CDE.

GA-based CDE, which gives optimum parameters for single and multi-carrier CR systems, were proposed by Newman et al. [21]. Using the weighted sum approach, many fitness functions were presented and optimized. The transmission variables set, i.e., the transmission power and modulation level for various transmission modes are reconfigured. Each scenario contains a primary objective of 80% weighting and a significantly lower secondary target. GA has the problem of getting stuck at local optimal solution and it takes around 500 iterations for the best value to converge.

The PSO was used for decision-making purposes to obtain parameter adaption for a multi-carrier CR system [22]. For four different modes of operation are used to solve the multi-objective optimization (MOO) problem. The performance of a real coded of the PSO algorithm was compared by the authors with the GA-based technique. This method provides higher stability and fitness value than standard GA methods.

The performance of the GA, PSO and ABC algorithms to develop a CDE was compared in [23]. Three types of transmission modes are evaluated: low power mode, multimedia mode and emergency mode, in addition the interference constraints are examined for primary and secondary users. In terms of mean optimal fitness and mean computation time, the results obtained from simulations are compared. A performance comparison of all modes indicates that CDE based on ABC is a better method than GA and PSO.

In the resolution of CDE problem with 10 subcarrier numbers, Zhao et al. [24] developed a novel mutated ACO (MACO) algorithm. The implementation of a weighted sum approach to maximize overall goal function addressed four different scenarios: low power mode, multimedia mode, emergency mode and balanced mode. In local minimal avoidance, the mutation process in MACO helps to improve its performance than the usual ACO algorithm. MACO evaporation rates were chosen at 0.8, 0.85 and 0.9 respectively, to simulate simulations. The fitness values achieved by MACO with 0.9 evaporation rate are better than GA and ACO base fitness values.

In order to optimize the transmission parameters in a CR system, Kaur et al. [25] presented SA-based CDE. The transmission parameters have been optimized to meet the user's diverse QoS requirements, such as reducing transmission power, bit error rate and interfering power while increasing spectral efficiency and throughput. Various transmission parameters, including power transmission, bandwidth, modulation level, time division duplexity and symbol rates, have been optimized for a range of objectives. SA-based CDE attains better fitness rates than the GA-based system, however SA require a comparably higher computation time and a greater number of generations to converge. Therefore, the SA-based CDE is only a good solution if the optimization work is not time-bound, and is not ideal for real time applications where the decision process needs to be relatively fast.

The above-mentioned work is extended in [26] in which the authors have utilized a BBO technique to solve the problem of optimization in the single CR system carrier. The two techniques used in BBO for searching for the optimal global value are migration and mutation. These mechanisms are further controlled by emigration and immigration rates. A comparative analysis of BBO and GA in different scenarios revealed that the fitness scores acquired using BBO are better than those obtained for conventional GA based CDE.

The performance of six evolutionary algorithms: ABC, GA, DE, BFO, PSO, and CSO has been tested by Pradhan et al. [13] for the solution of the CDE design problem. The task is to optimize certain communication goals for a single and multi-carrier CR system for parameter adaptations. These objectives are stated in terms of predefined fitness functions that reduce power consumption (for low power mode), minimize bit error rate (in an emergency mode) and improve throughput (for multimedia mode). From the simulation results, the CSO algorithm was identified as a fair choice for efficient CDE realization.

A modified whale optimization algorithm (MWOA) for the design of the cognitive radio system is proposed by Bansal et al. [27]. The random weight vector on location of humpback whales is used in this technique. It suggests the exploration and exploitation, and balance of these two phases in the search space. Results comparison of MWOA was carried out with BBO and SA. The results achieved using MWOA are found to be highly satisfying and need fewer iterations than the BBO and SA algorithms.

According to Dinesh et al. [28], as the wireless communication fields are developing day by day, the challenges faced are also increasing as well. The spectrum allotment is one of the significant difficulties in this area. Therefore, they proposed the use of modified Spider Monkey

Optimization to optimize the spectrum scheduling, which in turn improves the energy efficiency of the available spectrum. This delivers the optimal global solution and enhances functional requirements. A modified round robin approach is used to schedule spectrum by employing a packet flow with a packet queue in the interface controller. Performance measurements such as handoff, probability of false alarm, throughput, and success probability are analyzed. The results suggest that the system proposed performs well than the other existing methodologies.

An efficient metaheuristic algorithm is required in the work already undertaken to optimize the CDE design. The required algorithm must have fast processing speed and capability to provide a higher probability of detection for a licensed channel. This work aims to design an efficient cognitive decision engine optimizer for adaptation of transmission parameters in a multicarrier system using SLSSA discussed in next section.

3 Self-Learning Salp Swarm Algorithm (SLSSA)

3.1 Salp Swarm Algorithm (SSA)

Salp swarm algorithm (SSA) [29] is a swarm-based meta-heuristic optimization technique inspired by nature. Salps are jellyfish-like creatures that live in the deep ocean and the swarming behaviour of salps inspired this algorithm. The population of salps can be divided into two groups: leaders and followers. Leaders lead the entire population, while followers, either directly or indirectly, obey the leaders' orders. To move, the salps create a chain. The salps at the front of the chain are called leaders, while the remaining salps are called followers. Leader salps are assigned to the better half of the population. The remaining salps, on the other hand, are regarded followers.

The position of salp is an n-dimensional search space, in which n is the number of variables of a particular problem, as specified with other swarm techniques. The position of all salps is therefore stored in a 2-D matrix known as x. The food source is also assumed to be F in the search space as the target of the swarm. The following are the updated candidate solutions for leaders and followers.

Update of Candidate Solutions for Leaders:

The equation used to update the leader's position is:

$$x_{i,j} = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j), & c_3 \geq 0 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j), & c_3 < 0 \end{cases} \tag{1}$$

where $x_{i,j}$ indicates the *ith* salp's j-dimensional position (leader), F_j is the food-source location in the jth dimension, lb_j and ub_j indicate the lower and upper bound of jth dimension respectively, c_1, c_2, and c_3 represents random numbers. Eq. (1) shows that only with regard to the food source the leader upgrades his position. The c_1 is the main parameter in SSA as it equalizes the following exploration and exploitation capability:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{2}$$

where l and L are the current and maximum number of iterations respectively. The c_2 and c_3 parameters are the random numbers generated uniformly in the [0, 1] interval. They actually dictate whether the next position should be towards +ve or −ve infinity along with the step size in the jth dimension.

Update of Candidate Solutions for Followers

The solutions of leaders are used to update the candidate solutions for followers. For updating the candidate solutions for followers, a mathematical equation is applied as

$$x_{i,j}^{new} = \frac{1}{2}(x_{i,j} + x_{i-1,j}) \tag{3}$$

where i $\geq$ 2 and $x_{i,j}$ represents the jth dimension position of ith follower salp.

The position of the leader and the followers salp is updated with Eqs. (1) and (3). Because of c_1 parameter, the movement of the salp chain can explore and use the search space around both the food sources that are fixed and that are in motion [29]. Parameter c_1 reduces over the number of iterations adaptively so as to enable the algorithm to explore during initial stages and exploit at the end. Owing to this, SSA can avoid local optimum stagnation and determine the appropriate estimate of the optimal solution over the entire process of optimization.

3.2 Self-Learning Salp Swarm Algorithm (SLSSA)

To obtain its global optimum, a self-learning rule exploits the region in close proximity to the individual position [19]. The rule gives each learner the opportunity to expand their individual experience by search around them. This phase can be described as

$$x_{i,j}^{new}(k) = x_{i,j}(k)(1 + \lambda(rand - 0.5)) \tag{4}$$

where, $x_{i,j}^{new}(k)$ is the updated solution in the self-learning phase, λ is the self-learning factor that determines each individual's self-learning capability, and $rand \in [0, 1]$ is the random number generator. In this work, the value of λ is taken to be 3. Using greedy selection, update the solution vector $x_{i,j}(k)$. After the completion of self-learning phase, the updated $x_{i,j}(k)$ is used in the next iteration.

4 Transmission Parameters Optimization of CR System Using SLSSA

Transmission parameters are used by CR systems to control communication aspects. Five transmission parameters are employed as decision criteria for objective tasks in this employment. In a wireless communication scenario, the CR system will have to achieve numerous performance goals [25]. Various methods such as GA [21], SA [25], BBO [26] were applied to optimize CR systems design. For throughput maximization, interference minimization, bit error rate minimization, spectral efficiency maximization, and transmit power minimization, the nature inspired methods are utilized to achieve these goals. Tab. 1 lists the details of the above-said CR objectives.

Table 1: Objectives for the CR system

Name of the objective	Description
Power consumption minimization	To minimize the system power consumption
BER minimization	To minimize the BER of the transmitted information.
Throughput maximization	To maximize in data throughput of the system.
Interference minimization	To reduce the interference contributed by the radio
Spectral efficiency maximization	To maximize the frequency spectrum usage

Tab. 1 can be mathematically defined using five single objective attributes. The following are the single objective functions for a CR scheme with N autonomous subcarriers:

Power minimizing mode: The fitness function to minimize general power consumption is provided as

$$f_{min-power} = P_{avg}/P_{max} \tag{5}$$

where P_{max} is the highest transmitting power available and P_{avg} is the average transmitted power.

BER minimizing mode: in order to minimize the bit error rate, the fitness function can be expressed as

$$f_{min-BER} = log_{10}(0.5)/log_{10}(P_{BER}) \tag{6}$$

where P_{BER} is the quadrature amplitude modulation (QAM) BER.

Throughput maximizing mode: To attain maximum throughput, the fitness function can be formulated as

$$f_{max-throughput} = 1 - log_2(m)/log_2(m_{max}) \tag{7}$$

where m_{max} is the upper limit of the modulation index and m is the modulation index of a single carrier.

Interference minimizing mode: With an aim to minimize the effect of interference, the fitness function is given as

$$f_{min-inter} = \{(P_c + BW + TDD) - (P_{min} + BW_{min} + 1)\}/(P_{max} + BW_{max} + 100) \tag{8}$$

where BW is the single carrier bandwidth, and BW_{min} and BW_{max} are the highest accessible and the minimum required bandwidth.

Spectral Efficiency maximizing mode: To attain the maximum spectral efficiency, the fitness function is expressed as

$$f_{max-spec.eff} = 1 - (\mathrm{M} \times BW_{min} \times \mathrm{S})/(B + m_{max} + S_{max}) \tag{9}$$

where S is symbol rate and S_{max} is the upper limit of symbol rate.

For any mode or service type, one of the objectives is selected as primary and others are treated as secondary. There are several techniques available to solve such problems with multiple fitness functions. One of the most frequently used techniques is a weighted sum approach which is adopted in this work. This approach assigns a higher weight to the primary objective and lower weight values to all the secondary objectives. In general, the weighted sum approach for objective functions is provided as

$$\begin{aligned} f_{CR_objective} = {} & w_1 * f_{min-power} + w_2 * f_{min-BER} + w_3 * f_{max-throughput} + w_4 * f_{min-inter} \\ & + w_5 * f_{max-spec.eff} \end{aligned} \tag{10}$$

Based on the type of various modes of operation and battery levels, the assigned weight values are listed in Tab. 2.

5 Simulation Outcomes

SLSSA has been used on the CR system in this study to meet the optimization goals. Each simulation is run 30 times for sensitivity analysis for 2000 number of iterations with a population size of 30. The NBA, CS, TLBO, DA, GWO, and SSA algorithms were chosen to test the performance of the SLSSA algorithm. Tab. 3 shows the parameter settings for the algorithms utilized in this comparison. For each of the algorithms, we used a total of 30 search agents and 2000 iterations.

Table 2: Weight factors for CR system [30]

Mode	Weight factors for five modes
	[w1 w2 w3 w4 w5]
Power minimizing mode	[0.45 0.10 0.20 0.15 0.10]
BER minimizing mode	[0.10 0.50 0.10 0.10 0.20]
Maximizing throughput mode	[0.10 0.15 0.50 0.15 0.10]
Minimizing interference mode	[0.10 0.10 0.20 0.50 0.10]
Maximizing spectral efficiency mode	[0.10 0.15 0.15 0.10 0.50]

Table 3: Parameter settings

Algorithm	Parameters
TLBO	$NP = 30$; $D = 5$; $G_{max} = 2000$;
CS	$NP = 30$; $D = 5$; $G_{max} = 2000$; Probability $(p_a) = 0.25$
NBA	$NP = 30$; $D = 5$; $G_{max} = 2000$; $A = 0.5$; $r = 0.5$; $\alpha = \gamma = 0.9$; $f_{min} = 0$; $f_{max} = 1.5$
GWO	$NP = 30$; $D = 5$; $G_{max} = 2000$; $a = [2–0]$
DA	$NP = 30$; $D = 5$; $G_{max} = 2000$; $w = [0.4–0.9], s = 0.1, a = 0.1, c = 0.7, f = 1, e = 1$
SSA	$NP = 30$; $D = 5$; $G_{max} = 2000$
SLSSA	$NP = 30$; $D = 5$; $G_{max} = 2000$; $\lambda = 3$

Notes: Here, NP is number of populations, D is dimension of population, Gmax is number of iterations.

For CR system optimization utilizing SLSSA, five parameters were examined in the simulation setup, with the transmission parameter list presented in Tab. 4 [30]. Tabs. 5–9 show the optimum values as well as the transmission parameters of the five objective functions for NBA, CS, TLBO, DA, GWO, SSA and SLSSA. The fitness values achieved by the SLSSA are clearly superior to those attained by the NBA, CS, TLBO, DA, GWO, and SSA in three examples, and very competitive in the other two. As shown in Figs. 1–5, the convergence rate for SLSSA is also better than the other algorithms.

Table 4: Transmission parameter list

Parameter name	Value
Transmit power	0.1 to 2.4808 mW
Modulation type	QAM
Modulation index (MI)	2–256
Bandwidth (BW)	2 and 32 MHz
Time division duplexing	25% and 100%
Symbol rate	125 Ksps to 1 Msps

Table 5: The performance of simulated algorithms for CR in Power minimizing mode

Algorithm	Transmit power	Modulation index	Bandwidth	TDD	Symbol rate	Best fitness value achieved
TLBO	4.419092134786	256	2	25	1000	0.0228772297371797
CS	4.419092186996	256	2	25	1000	0.0228772297371796
NBA	4.419092111489	256	2	25	1000	0.0228772297371797
GWO	4.419093763176	256	2	25	1000	0.0228772297371796
DA	4.419092186996	256	2	25	1000	0.0228772297371802
SSA	4.419090540974	256	2	71.227858	1000	0.0228772297371798
SLSSA	4.417647469714	256	2	25	1000	**0.0228772286163529**

Note: Best values are given in bold.

Table 6: The performance of simulated algorithms for CR in BER minimizing mode

Algorithm	Transmit power	Modulation index	Bandwidth	TDD	Symbol rate	Best fitness value achieved
TLBO	36.218020572198	256	2	25	1000	0.0313254493188997
CS	36.218020655322	256	2	25	1000	0.0313254493188916
NBA	36.218020421591	256	2	25	1000	0.0313254493188998
GWO	36.218095978073	256	2	25	1000	0.0313254493189077
DA	36.218020655322	256	2	25	1000	0.0313254493188999
SSA	36.218032101506	256	2	83.159391	1000	0.0313254493188998
SLSSA	36.218017903564	256	2	25	1000	**0.0313254467296183**

Note: Best values are given in bold.

Table 7: The performance of simulated algorithms for CR in Maximizing throughput mode

Algorithm	Transmit power	Modulation index	Bandwidth	TDD	Symbol rate	Best fitness value achieved
TLBO	17.531329158313	256	2	25	1000	0.0161197040240226
CS	17.531329089409	256	2	25	1000	0.0161197040240226
NBA	17.531328868460	256	2	25	1000	0.0161197040240225
GWO	17.531184083205	256	2	25	1000	**0.0161197040240224**
DA	17.531329089409	256	2	25	1000	0.0161197040240226
SSA	17.531337043294	256	2	90.664949	1000	0.0161197040240232
SLSSA	17.531709851516	256	2	51.883459	1000	0.0161197040242182

Note: Best values are given in bold.

Table 8: The performance of simulated algorithms for CR in Minimizing interference mode

Algorithm	Transmit power	Modulation index	Bandwidth	TDD	Symbol rate	Best fitness value achieved
TLBO	13.480433141510	256	2	25	1000	0.0127781074462338
CS	13.480433136680	256	2	25	1000	0.0127781074462338
NBA	13.480433308669	256	2	25	1000	0.0127781074462337
GWO	13.480095745371	256	2	25	1000	0.0127781074462339
DA	13.480433136680	256	2	25	1000	0.0127781074462338
SSA	13.480369896665	256	2	63.193352	1000	0.0127781074462338
SLSSA	13.477204142167	256	2	99.860623	1000	**0.0127781074462333**

Note: Best values are given in bold.

Table 9: The performance of simulated algorithms for Maximizing spectral efficiency mode

Algorithm	Transmit power	Modulation index	Bandwidth	TDD	Symbol rate	Best fitness value achieved
TLBO	17.531329149315	256	2	25	1000	0.0161196664981725
CS	17.531329150164	256	2	25	1000	0.0161196664980734
NBA	17.531328866958	256	2	25	1000	**0.0161196664980498**
GWO	17.531328991404	256	2	25	1000	0.0161196664980499
DA	17.531329150164	256	2	25	1000	0.0161196664981263
SSA	17.531369474968	256	2	81.48074	1000	0.0161196664981241
SLSSA	17.531348503729	256	2	25	1000	0.0161196664981152

Note: Best values are given in bold.

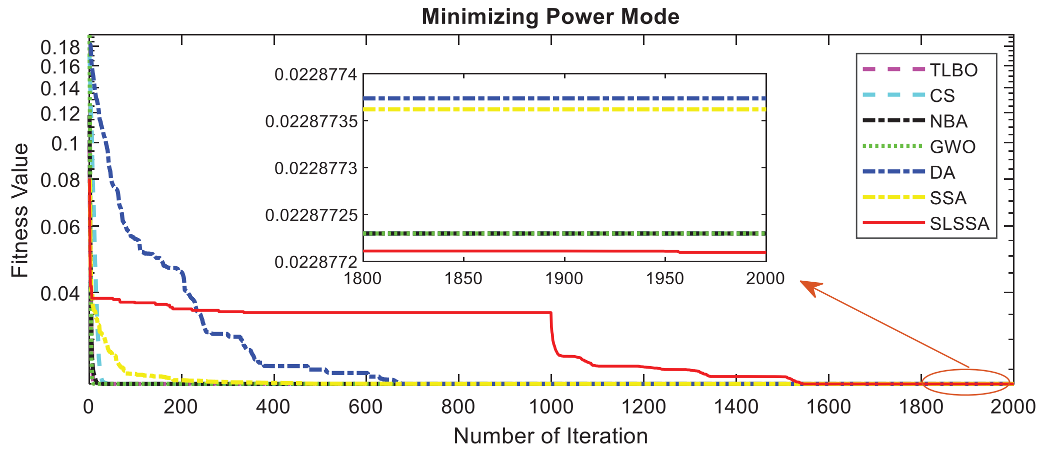

Figure 1: Convergence characteristics for minimizing power mode operation

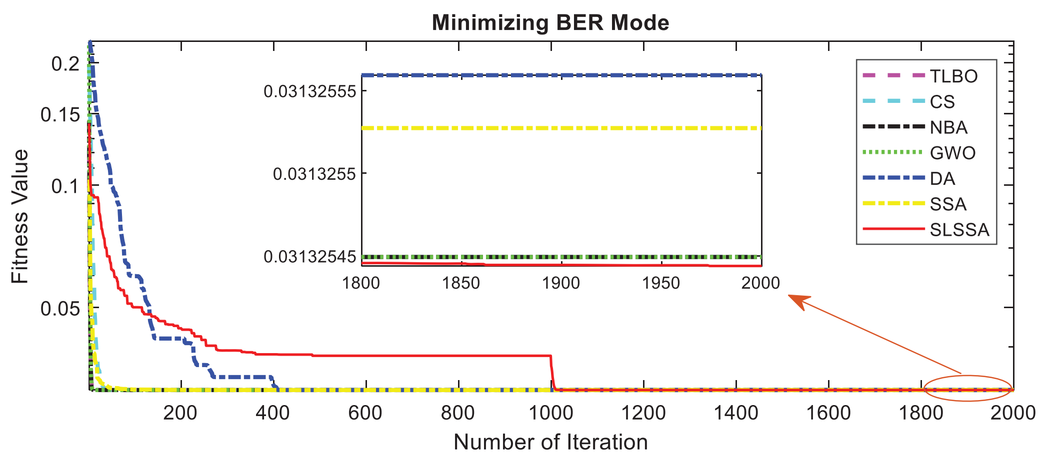

Figure 2: Convergence characteristics for minimizing BER mode operation

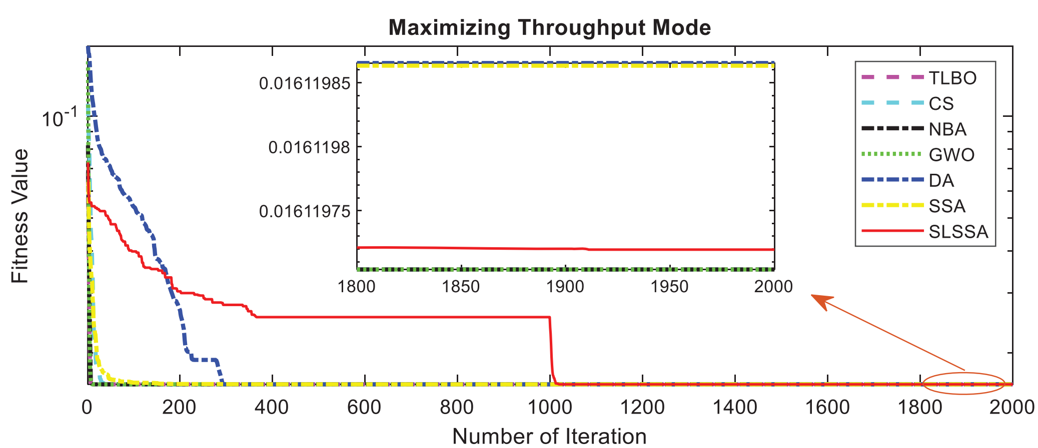

Figure 3: Convergence characteristics for maximizing throughput mode operation

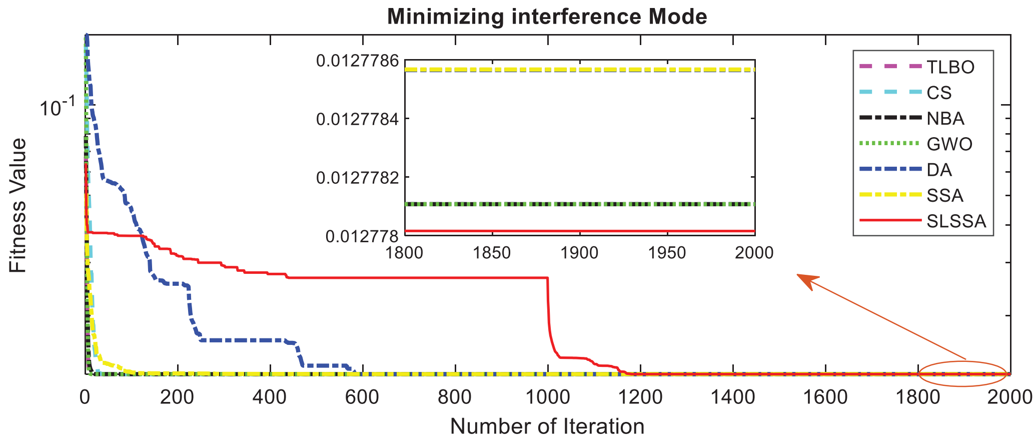

Figure 4: Convergence characteristics for minimizing interference mode operation

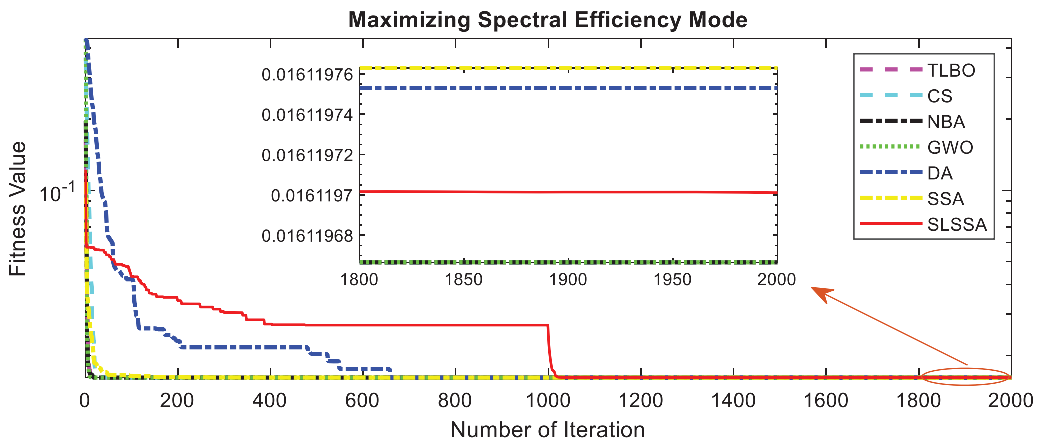

Figure 5: Convergence characteristics for maximizing spectral efficiency mode operation

6 Conclusion and Future Directions

CR is a potential solution for overcoming the difficulty of rising wireless applications requiring additional spectrum. This work is focused on the adaptation of different parameters of a CR system so that the overall transmission and sensing performance of the system can be improved. As meta-heuristic algorithms offer numerous advantages over classical mathematical approaches, performance of these algorithms is investigated to solve the problem of parameter reconfiguration. In this work, an optimization problem is studied to reconfigure the transmission parameters for the data transmission scenario of a CR. Further, the adaptation of transmission parameters by CDE is carried out for a multicarrier CR based system employing SLSSA, in that the multi-objective optimization problem is dealt with the weighted sum method. Five different transmission scenarios are considered each supporting different user requirement and radio battery level. SLSSA algorithm provides the best solution for most of the transmission scenarios of CR system.

In future, the problem of CDE design can be studied for other smart networks such as home area networks, smart grids etc. through advanced meta-heuristic schemes. Advanced meta-heuristic optimization techniques can be investigated for transmission parameter adaptation to realize green radios that support different transmission modes with the application of highly efficient Power

Amplifiers. The idea of energy harvesting based cooperative spectrum sensing with meta-heuristic techniques has not been explored yet and has a wider scope to probe in.

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