European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 7, Issue 4, 2020

Grey Wolf Optimization based Cognitive Radio Engine Design

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Abstract– Cognitive radio appears to be a natural solution to the problems of scale and complexity resulting from the great popularity of wireless communications and the evolution of radio technologies. A cognitive radio is an intelligent agent capable of adapting to its operational context to respect the regulatory framework controlling access to the spectrum, satisfy the user's needs in terms of quality of service, and ensure optimized management of available resources (radios, networks and equipment).This new paradigm is directly linked to the development of embedded intelligence, the subject of this paper.

In this paper, we detail the design of a cognitive engine (CE) structuring the reasoning and learning operations necessary for the supervision of the dynamic reconfiguration process.

It is noted that supervised and unsupervised learning methods have been projected for various learning tasks.This paper presents ametaheuristic that is Grey Wolf Optimization (GWO) as approximate methodfor the optimization of fitness function of proposed cognitive engine. In order to establish performance evaluation of CRaccording to different criteria that we have set, such as the bit error rate (BER), output power and channel attenuation.

Keywords– BER, CR, CE, GWO, PU, SU, etc.

1. Introduction

Cognitive radio (CR) is a technological concept pushing towards a total and autonomous adaptation of equipment with regard to their operational context. A cognitive radio relies on intelligent observation of its environment to adopt the best course of action in all circumstances using reactive and proactive actions [1]. She makes her decisions in the best interest of the user and the network and she learns from her experiences to always improve her performance. Radio thus goes from a simple blind executor of predefined protocols to a cognitive agent, sensitive to the radio domain and autonomous [2].

Cognitive radio has attracted a lot of attention since its introduction in 1999 by Mitola [3]. Mitola's vision projects the concept far into the future by considering the radio terminal as a personal assistant capable of anticipating the needs of the user in order to respond to them in the best way. This futuristic vision has since given way to more technological visions allowing better organization of research efforts on the subject [4]. We note, however, that it has taken the community some time to agree on the definition and expected properties of cognitive radio [5] [6] [7]. Still now, it is preferable to reason in terms of degrees of cognition to distinguish the solutions proposed according to their intrinsic capacities [6].

Cognitive radio remains a very broad and strategic research subject for any actor working in the telecommunications field. The concept of cognitive radio has given birth to a large number of particularly promising applications such as [8] [9]:

- **Opportunistic access to the spectrum:** Maximize spectral efficiency by dynamically allocating frequencies and effectively managing interference (received and transmitted) while respecting the regulatory framework.
- **The cognitive design of the radio link:** Optimizing the performance of the radio system by selecting the most appropriate signal processing blocks.
- **Selection of the best radio access technology:** Identify the access network that best meets the user's needs at the lowest possible cost.
- **Adapting the topology of a network:** Increase the coverage and capacity of a network through cooperation between radios.

Given its scope, cognitive radio is a highly multidisciplinary subject requiring skills in signal processing, network, statistical analysis, software and hardware engineering, autonomous decision making, and artificial learning to some name. It also requires revisiting spectrum regulation [10] as well as the economic models developed for wireless communications [11].

The cognitive behavior of a radio is due to the introduction of a cognitive engine structuring the modeling, decision-making and learning operations necessary for dynamic control of the reconfiguration process. The communication system feeds the cognitive engine with the information it collects on its operational context (e.g. measurements on the radio environment, performance indicators, disseminated policies, remaining battery level). The cognitive engine analyzes user and operator requirements, regulatory regimes and the physical link in order to identify the design objectives and applicable constraints. It then uses this understanding of the context to adapt the parameters of the protocol stack of the communication system.

The regulatory framework is defined using policies that memorize spectrum access constraints in machine-understandable language. Policies are disseminated locally and constraints can change depending on time and place. The radio must constantly respect the regulatory framework. For this, it has an inference engine (policy engine) capable of blocking any solution that violates local regulatory rules. The inference engine is a cognitive component applying deductive reasoning from information expressed in standardized machine language. The inference capabilities of the engine can be used for other activities. For example, the cognitive engine can call upon it to analyze the possibilities of reconfiguring communicating objects, to identify operational objectives, or even to propose an adapted communication strategy. The inference engine will be used more or less intensely depending on the cognitive approach adopted.

Cognitive Radio Engine

The operating principle of the cognitive engine can be summarized in two phases (see Figure 1 [12]). In a first phase, sensors collect and supply the cognitive engine with information relating to the operational context of cognitive radio. The latter includes information concerning the electromagnetic environment (spectral occupancy, channel characteristics, etc.), the regulation policies in force, material resources, user preferences, remaining battery level, etc. Subsequently, this information is exploited by an intelligent subsystem which analyzes it in order to find the most suitable configuration for the current context.

The set of possible solutions or configurations represents what is called in the literature a decision space. The latter is defined by three dimensions or constraints, namely: environmental constraints, user constraints and equipment constraints.

1. Environmental Constraints

Since a cognitive radio is wireless equipment operating in an electromagnetic environment, the space for possible configurations is limited by:

- The physical and natural characteristics of the RF environment such as noise, multipath fading and shadows.
- The rules of regulatory authority such as for example the allocation of frequencies, tolerated interference, etc.
- The current state of the RF environment at a given time, including for example the load on the channel and the activities of surrounding users.

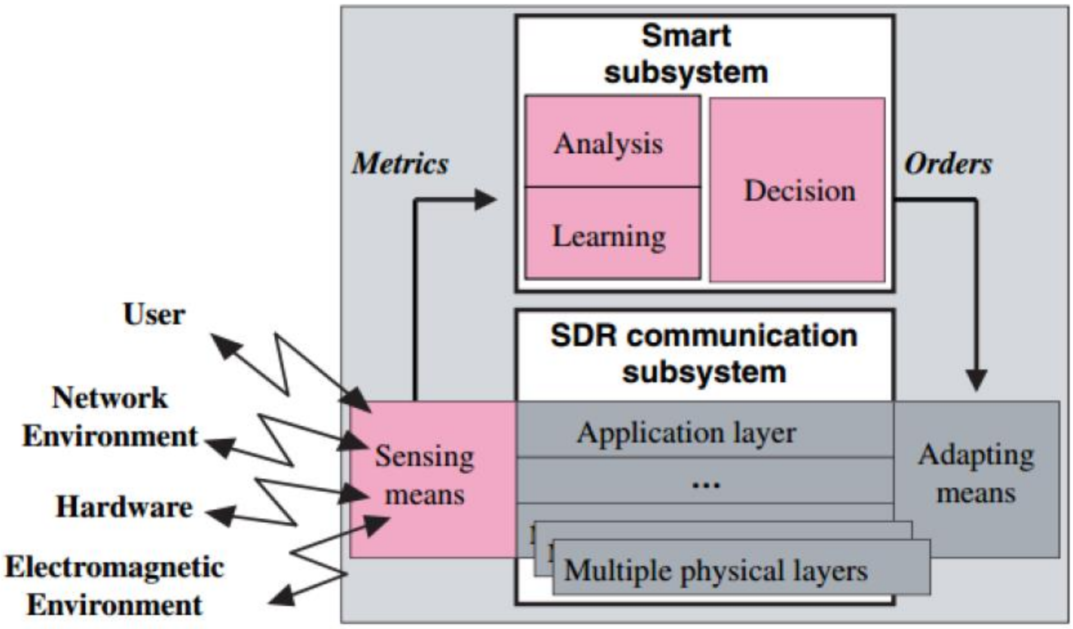

Figure 1: Synoptic diagram of a cognitive radio engine [12]

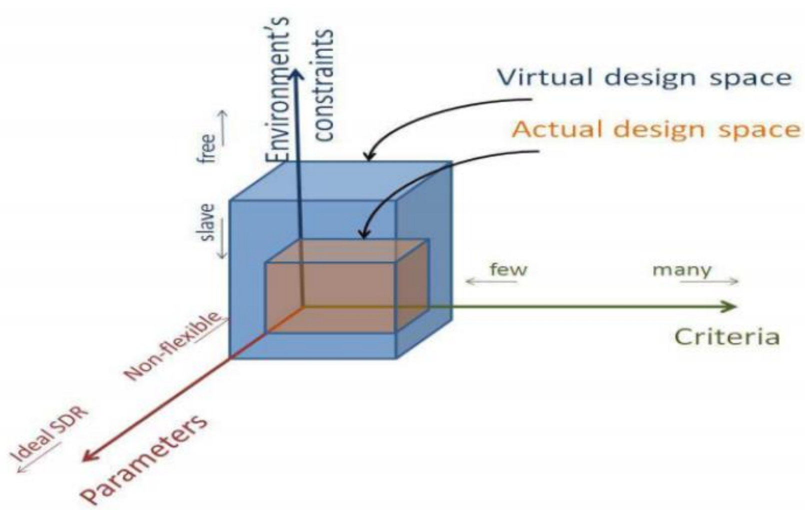

Figure 2: A conceptual diagram of the decision space of a cognitive engine [13]

2. User Constraints

These are the expectations of the user in relation to the quality of service he hopes for. In fact, each type of application has its own characteristics, for example voice communication is sensitive to the speed factor while a file transfer requires a low error rate. Thus, according to the different modes of use of the equipment, the needs of the user can vary depending on the nature of the service requested or on other factors such as energy consumption.

3. Equipment Constraints

It is commonly assumed in the literature that cognitive radio equipment is based on so-called ideal software radio. This means that radio is endowed with flexibility and complete independence from the platform on which it is implemented. This technology has not yet been developed to date. Thus for a real application, the limitations of software radio restrict the space of configurations achievable for cognitive radio.

The cognitive engine is an artificial intelligence agent that performs the modeling, learning and optimization processes required to reconfigure the CR itself. The cognitive engine takes information from the service management layer, the radio domain and the policy engine through different interfaces. The policy engine receives information related to the policies of the policy domain set by the communications administration of the country in question. This information helps the cognitive radio to decide on the permitted solutions and blocks any solution that breaks local regulations.

For almost two decades, CE designers have been constantly working to develop better learning techniques for CR. In general, they have borrowed ideas from machine learning and artificial intelligence to design their CE. Notable examples include artificial neural networks (ANN) [14], genetic algorithms (GA) [15]and reasoning based on cognitive engine case [16]. In addition, other techniques such as particle swarm optimization (PSO) [17] and ant colony optimization [18] are also used to frame the cognitive radio engine.

This paper presents a framework of cognitive radio engine using a metaheuristic approach; Grey Wolf Optimization. Section two presents the implementation of proposed cognitive radio engine design. Results are presented in section three trailed by the conclusive remarks in the section four.

2. Proposed Methodology

In the field of cognitive radio, the primary user (PU) who is in possession of a license is free to access the spectrum at any time via his frequency bands, unlike the secondary user (SU) which can access only frequency bands not used by the (PU), according to the criterion of cooperation between the two without producing interference.

A cognitive engine usually uses metaheuristics for its operation, so we have used GWO approach. The objective is to show the interest of parallelizing an exact method in order to improve spectrum management within the framework of a cognitive radio network. We therefore, in the following, present the results obtained during the realization of this work.

4. Objective Function (Fitness Function)

It is a function which is used to determine the best solution to a combinatorial optimization problem that is either of the maximize type or the minimize type until the most favorable solution is obtained. In our case the utility of this function is to maximize the cost "benefit for the primary user" and also the number of (SU) satisfied and minimize the processing time "response time to secondary users".

The following parameters:

- n: the number of SU.
- m: the number of free channels possessed by the PU.
- W: an array of size n. $W[i]$ is the number of channels requested by SUi.
- C: a size chart n. $C[i]$is the price offered for $W[i]$ by SUi.
- The function to be optimized is:

$$\text{Max} \sum_{i=0}^{n-1} C[i] \tag{1}$$

- The constraint to be respected is:

$$\sum_{i=0}^{n-1} W[i] \leq m \tag{2}$$

The fitness function optimized by the proposed GWO algorithm explained in the following heading.

A. Grey Wolf Optimization

The Grey wolf optimizer algorithm is proposed in [19]. When the grey wolf optimization method is experimented with the 29 database functions and its result is compared with other meta-heuristic approaches, it is seen that the Grey wolf Optimizer algorithm has an outstanding performance than other meta-heuristic methods [19].

The leader of the pack is called as alpha. It can be a male or female which makes decision on hunting, wake-up time, sleeping place etc. The rules/orders made by alpha are to be obeyed by the rest of the pack/group. Hence alpha possesses the to-most level in the hierarchy [19].

The next order in the grey wolf pack is beta. The beta wolf is responsible for advising the alpha in decision making process and to make alpha's decision to be followed by other lower level pack. Beta can be male or female. He/she is responsible to maintain discipline among the pack. In case of alpha's death or similar circumstances, beta is the appropriate candidate to take alpha's place.

The lowest level in the grey wolf hierarchy is omega. This category of wolf is dominated by all other wolves and has to surrender to the dominant wolves. Omega wolves have to follow all the orders given by the superior wolves. They are even allowed to eat at last when all other wolves finish eating. From this, it seems that omega wolves are not as important as other wolves.

Another level is delta level in the hierarchy. Delta wolves come at lower level than alpha and beta but at higher level than omega. Delta wolves have to surrender in front of alpha and beta but they dominate omega. This category of wolves is comprised of caretakers, elders, hunters and scouts. So there overall responsibility is to safeguard the pack and take care of pack concerning their heath and food. The hierarchy of grey wolves is shown in Figure 3.

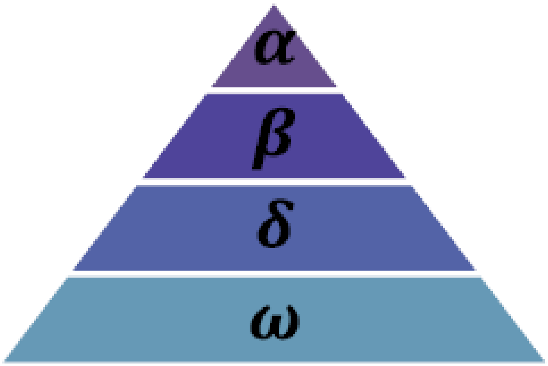

Figure 3: Grey Wolf Hierarchy [19]

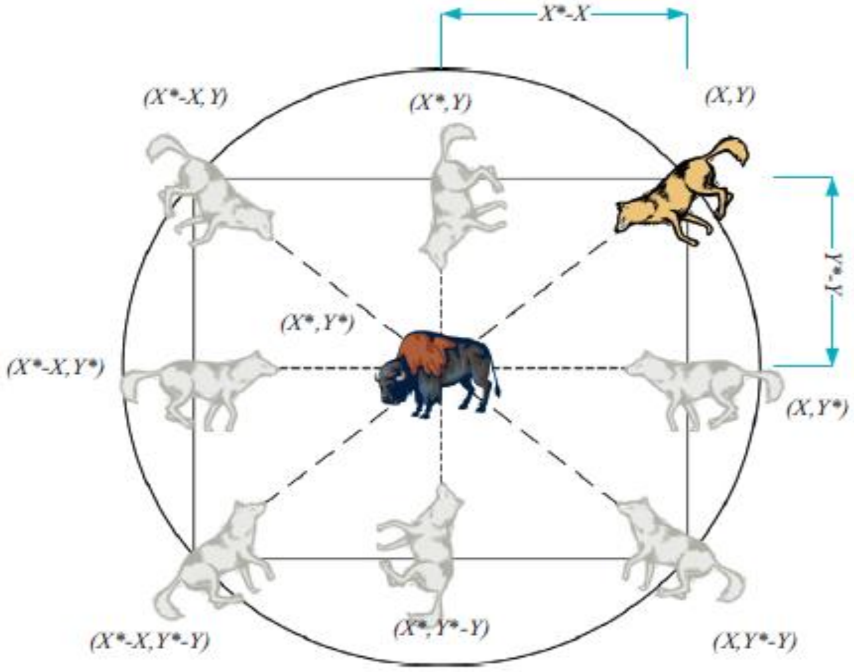

Figure 4: Possible hunting locations and encircling behaviour of wolves [19]

The best solution in mathematical representation of social hierarchy of wolves while designing GWO is considered to be alpha 'α'. The 2nd and the 3rd best solutions are 'β' and 'δ' respectively. The hunting decisions are taken by α, β and δ wolves whereas 'ω' (omega) wolves obey above three wolves. Figure 4 depicts the possible hunting locations and encircling behavior of wolves.

The encircling behaviour of the wolves around its prey can be represented mathematically as follows:

$$\vec{D} = \left|\vec{C}.\vec{X}_p t - \vec{X}(t)\right| \quad (3)$$

$$\vec{X}(t+1) = \vec{X}_p t - \vec{A}.\vec{D} \quad (4)$$

Where, X is the position vector of the wolf.

A and C are coefficient vectors

t is the current iteration

Grey Wolf Optimizer (GWO) Algorithm

1. Grey wolves wander in search of its prey depending on the alpha, beta and delta positions. They go away (divergence) from each other in search of a prey and gather again (convergence) while attacking the prey [19]. This divergence can be mathematically given by A and convergence is represented by C.

$$\vec{A} = 2.\vec{a}.\vec{r}_1 - \vec{a} \quad (5)$$

$$\vec{C} = 2.\vec{r}_2 \quad (6)$$

Where, $\vec{r}_1$ and $\vec{r}_2$ are random vectors:

2. The initialization of GWO population is given by at counter iteration t=0:

$$X_i = (1,2,3 \ldots \ldots \ldots \ldots n) \quad (7)$$

3. Further A, C and a are also initialized
4. Now the fitness function for each searching agent is evaluated and is represented as:
   X_α denotes best searching agent
   X_β denotes 2nd best searching agent
   X_δ denotes 3rd best searching agent
5. If the total no. of iterations is given as $t = n$, then
   For $(t = 1; t \leq n)$
   Using above equations update the position of searching agents
   End for
6. Update A and C coefficients
7. Evaluate fitness function for each searching agent
8. Update $X_\alpha, X_\beta, X_\delta$
9. Set $t = t + 1$ (iteration counter increasing)
10. Return best solution X_α

GWO Working

1. The GWO resolves the optimization problem by generating the best solutions available during iterations.
2. The encircling behaviour gives an idea about the neighbouring circle around the solution which could be further extended into sphere (as shown in Figure 5).

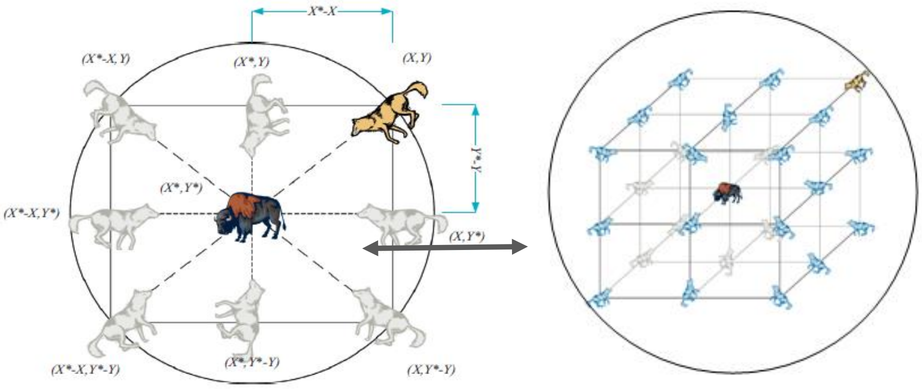

Figure 5: Extension of encircling shape into sphere

3. A and C coefficient vectors help solutions to have random radii hyperspheres.
4. The hunting behaviour permits the solution to define the exact location of the prey.
5. Values of a and A are responsible for exploitation and exploration.
6. If the value of A decrease, then total number of iterations are equally divided and assigned for exploitation and exploration respectively.

3. Simulation Results

The graphs below represent the results obtained:

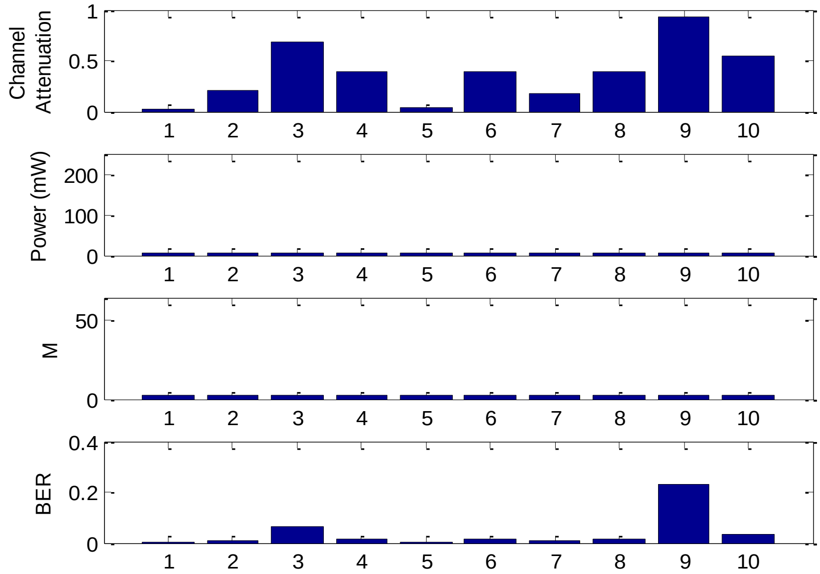

Figure 6: Channel attenuation, power, modulation and BER in low power mode using GWO

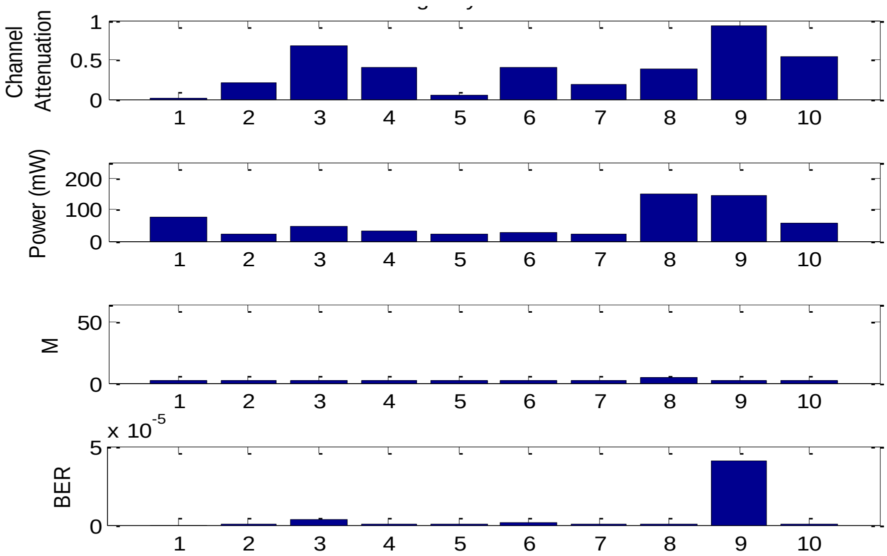

Figure 7: Channel attenuation, power, modulation and BER in emergency mode using GWO

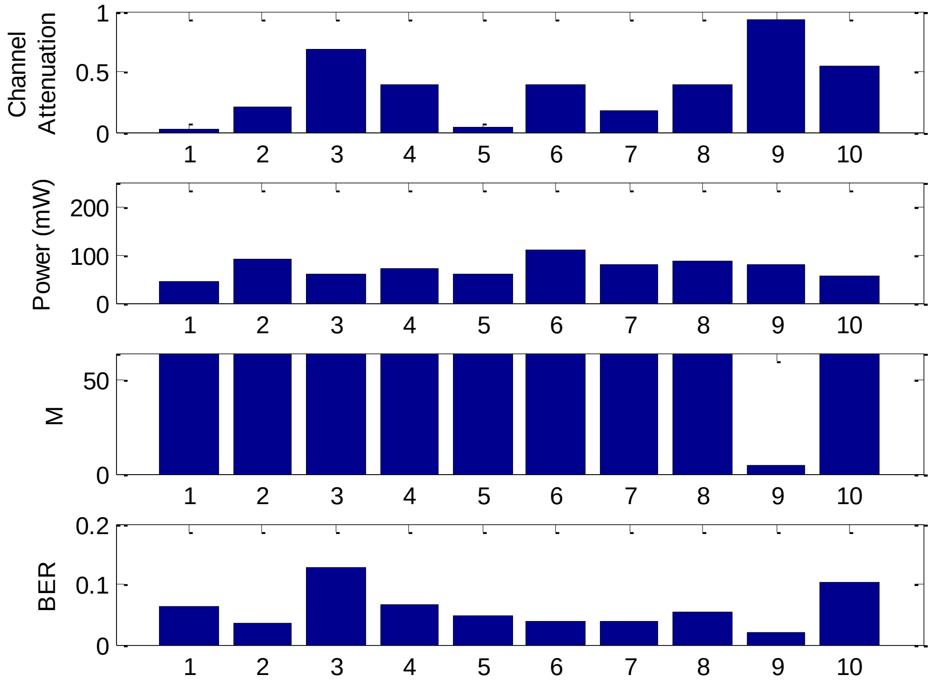

Figure 8: Channel attenuation, power, modulation and BER in multimedia mode using GWO

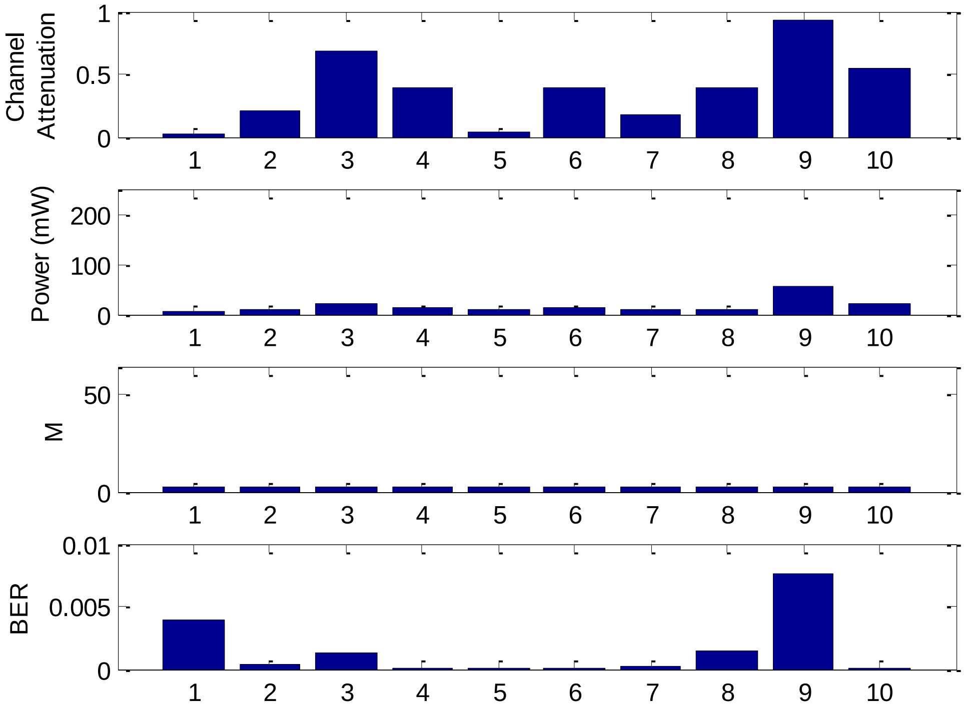

Figure 9: Channel attenuation, power, modulation and BER in balanced mode using GWO

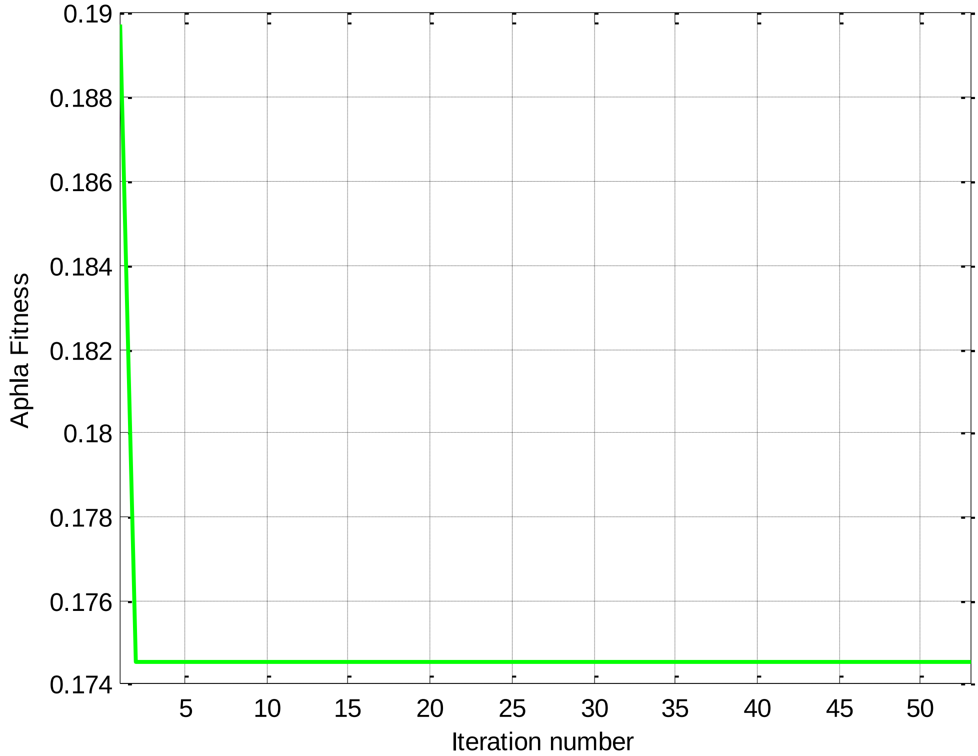

Figure 10: Iteration graph of GWO

4. Conclusion

The various researches that have been conducted on cognitive radio have made it possible to respond to challenges related to its implementation and its application to innovative technologies.

Cognitive radio is a significant approach that solve spectrum saturation problems and access conflicts.

The exchanges that are made during a spectrum access negotiation between the primary and secondary users are observed as a delicate operation and also as a combinatorial optimization problem. Thus, in our study, we focused on a solution that could nevertheless give a better performance to this negotiation, our work is built the metaheuristics which allow to obtain quickly good results. Metaheuristic, GWO algorithm that represents the optimization method. Other metaheuristic-based method can also be used in future to enhance the performance.

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