EVOLUTIONARY NEURAL NETWORKS ALGORITHM FOR THE DYNAMIC FREQUENCY ASSIGNMENT PROBLEM

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ABSTRACT

Wireless communication is used in many different situations such as mobile telephony, radio and TV broadcasting, satellite communication, wireless LANs, and military operations. In each of these situations a frequency assignment problem arises with application-specific characteristics. Researchers have developed different modelling ideas for each of the features of the problem, such as the handling of interference among radio signals, the availability of frequencies, and the optimization criterion.

This paper presents a new approach for solving the problem of frequency allocation based on using initially a partial solution respecting all constraints according to a greedy algorithm. This partial solution is then used for the construction of our stimulation in the form of a neural network. In a second step, the approach will use searching techniques used in conjunction with iterative algorithms for the optimization of the parameters and topology of the network. The iterative algorithms used are named hierarchical genetic algorithms (HGA).

Our approach has been tested on standard benchmark problems called Philadelphia problems of frequency assignment. The results obtained are equivalent to those of current methods. Moreover, our approach shows more efficiency in terms of flexibility and autonomy.

KEYWORDS

Frequency assignment, combinatorial optimization, genetic algorithms, neural networks.

1. INTRODUCTION

Current wireless networks are characterized by a static spectrum allocation policy, where governmental agencies assign wireless spectrum to license holders on a long-term basis for large geographical regions. Recently, because of the increase in spectrum scarcity, in particular spectrum bands, and due to large portions of the assigned spectrum is used sporadically, leading to underutilization of a significant amount of spectrum [5], the most interesting and pertinent issue for radio spectrum is dynamic spectrum assignment.

Dynamic spectrum assignment problem is one of the most studied problems in the literature, particularly multiple variants algorithms are proposed for solving this problem [1], [2], [10], [13], [15], [16], [17], [18], [19] and [20].

The problem starts from some networks initial connections (namely robust) to develop progressively the subsequent connections according to the operational change of

DOI : 10.5121/ijcsit.2011.3304

communication needs and taking into account the constraints of disturbances with all initial connections.

Constraint satisfaction techniques are a board family of greedy algorithm that can be used to solve this problem. The algorithm guarantees to find an optimal solution using a process of a partial assigning first, fixing the assignment and then extending the assignment to the full problem. Furthermore, the algorithm guarantees an exhaustive search in the search space of a complete solution. But in some cases it can be impossible or impractical to solve these problems completely and the time and effort required to the search may be prohibitive [18]. The most straightforward way for solving such problems using constraint satisfaction techniques would be to represent each call as a variable (belonging to the domain of available frequencies), then to solve the problem as a generalized graph-colouring problem. However, solving real-life, large-scale problems' using this simple formulation seems rather difficult without avoiding the symmetries between calls within one cell [19]. On the other hand, these methods are, theoretically and experimentally, outperformed by existing techniques and the computation complexity of searching for the optimum solution in the dynamic channel assignment problem grows exponentially with the problem size.

Unlike greedy methods, meta-heuristics don't seek to find complete solutions to the problems but an optimal solution with a good compromise in a reasonable time. These techniques are nowadays widely used; such as the following techniques that have become popular: Simulated Annealing (SA), Taboo search (TS), and Genetic Algorithms (GAs).

The taboo search technique is based on the intelligent search and embraces more efficient and systematic forms of direction of search, such as memorizing and learning. By a dynamic neighbourhood search the TS looks for specified instance of the problem with a finest neighbour from in this dynamically modified neighbourhood, and visits a sequence of locally best configurations following the neighbourhood function that progress the current solution in terms of the global cost function. One of the most vital components of the method is a Taboo list, it is a unique short-term memory with the purpose of maintaining a selective history, composed of earlier encountered solutions or more normally pertinent attributes of such solutions [17].

The simulated annealing technique (SA) is a stochastic computational technique that evolved from statistical mechanics and has a direct similarity with thermodynamics, particularly with the manner that liquids freeze and crystallize, or metals cool and anneal [20]. Used for solving big optimization problem such as frequency assignment problem, by determining the global minimum value of the objective function with various degrees of freedom subject to the problem in a reasonable amount of time. It fails reach a minimum energy state but rather higher energy state, in the mathematical sense, to a sub-optimal solution created by iterative improvement or hill-climbing. This technique is more efficient than the Taboo search technique; its big advantage is its capability to move to states of higher energy. On the other hand the Taboo Search (TS) presented her does not support this feature. This is why TS cannot run away from likely local minima and normally results inferior configurations. Taboo memory is not a mechanism to overcome local minima but a method to evade cycling that is to create a larger amount of possible configurations in less iteration [20].

Another way of the problem resolution consists of representing a cell as a variable that has a wide area of values, and tries to determine the value of this variable step by step instead of determining a value for this variable at one time.

Recently, neural networks have been considered one of these ways for the channel assignment problems. This technique is based on the behaviour of neurons in the brain; as it is based on a biological process rather than a physical one. The advantages of the algorithm are its inherent

parallelism, its property to detect areas of different problem difficulty without heuristics, and the possibility of extending the algorithm to 'soft' interference criteria. For example, it may be possible to rank the interference conditions according to their probability so that in case of an insufficient number of available channels, the incompatibilities with the lowest probability of excess interference are violated first. One major disadvantage of a neural network is that it gives the local optimal value rather than the global optimal value. And the solution varies depending on the initial values. [10]

Genetic Algorithms (GA) have an advantage over Neural Networks or Simulated Annealing in that genetic algorithms are generally good in finding very quickly an acceptably good global optimal solution to a problem [9]; even if, genetic algorithms do not guarantee to find the global optimum solution to the problem. In this algorithm, the cell frequency is not fixed before the assignment procedures as in the previously reported channel assignment algorithm using neural networks [10]. The average generation numbers and the convergence rates of GAs are shown as a simulation result. The combination of two points' crossover and selective mutation technique provides better results. Genetic algorithms are expensive in computing time, as they handle multiple solutions simultaneously.

The objectives of this paper are twofold. First, present and formulate the problem. Second, establish a perspective of resolution based on the application of hierarchical genetic algorithms (HGA) for the optimization of neural networks. The neural networks are initialized by a set of stimuli generated by the Degree of Saturation (D-Satur) as a greedy algorithm.

The HGA combined with an iterative approach allow inserting dynamically the new chromosome in the basin of a changing population.

2. PROBLEM FORMULATION

The dynamic allocation resources problem in a wireless network tends, starting from a network of initial links, to:

- Establish gradually the subsequent links, by assigning a frequency to each link in a given spectrum according to the operational change of operating environment and communication needs,
- Satisfy both duplex constraints, co-site constraints and lockage constraints, and
- Take into account the constraints of disturbance with the set of initial links.

The problem is formulated by a network of constraints with the following data:

- $X = \{x_1, x_2, x_3, \ldots, x_n\}$ set of n distinct cells.
- $L = \{l_1, l_2, l_3, \ldots, l_p\}$ all p available links (with n=2p), and
- $D = \{D(l_1), D(l_2), D(l_3), \ldots, D(l_p)\}$ all p areas of channels available for each li, i=1,…,p.

The set of constraints is represented by a p*p matrix called matrix of compatibility $C=[C_{ij}]$, i = 1, …, p and j = 1, …, p.
In its static version and for a set of p links and a set of k frequencies, the problem is to find a frequency plan $F = \{f_1, f_2, \ldots, f_p\}$ such that $| f_i - f_j | \geq C_{ij}$, where fi in $D(l_i)$, is the frequency of link li, and fj in $D(l_j)$, the frequency of l_j and Cij the required frequency gap. An optimal solution is sought to facilitate the subsequent addition of new links [2].

2. RESOLUTION APPROACH

To solve the problem, the proposed approach is established by using a greedy algorithm (named Degree of Saturation), to set an initial assignment respecting all constraints and minimizing the affectation cost. This initial assignment provides the minimum number of used frequencies and assembles, to the maximum, the frequencies in the lower part of the spectrum while avoiding deadlock.

Degree of Saturation (D-satur):

At each step, i, based on a rule of thumb calculation, we determine the number of unauthorized frequencies, in this step, for each link xj (called degree of saturation). Then, we assign the smallest possible frequency to the link of higher degree of saturation. In case of several links having the same degree of saturation, we relay on the degree of separation of these links. This is the weighted sum of the bond ij with its current neighbours.

As a case study example, let us consider that we want to install a set of five base stations to cover a rural area. In the following graph, vertexes represent the links (numbered from 1 to 5) and the valuation of the edges represents the minimum frequency interval required between the two links corresponding to the end vertexes of this edge. We should determine for each link of the graph a frequency on the interval [1 ... k] minimizing k.

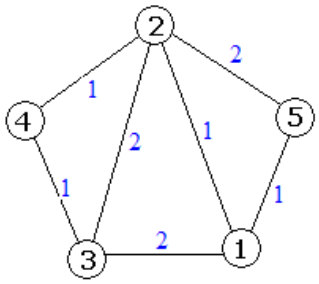


Fig1a: Example of network for five base stations [1]

Table 1 shows the degrees of separation D(xj) of each link xj in this graph. These degrees of separation represent the sum of valuations of the incident edges for each summit. They are compiled once and for all. The second table is generated dynamically. The degree of saturation di(xj) in step i is used as a criterion for selecting the station that we will assign. These degrees are determined from the intervals not allowed for stations that are not yet affected; they are listed in the third table 3.

Step I:

Table 1: Table of degree of separation

Xj	D(Xj)
1	4
2	6
3	5
4	2
5	3

Table 2: Table of degrees of saturation

i		1	2	3	4	5
Degrees of saturation	di(1)	0	1	4		-
	di(2)	0	-	-	-	-
	di(3)	0	2	-	-	-
	di(4)	0	1	2	2	2
	di(5)	0	2	2	3	-
Choices	xj	2	3	1	5	4
	D (xj)	1	3	5	3	2

Table 3: Table of intervals not allowed for stations.

xj	intervals unhallowed
1	[1] ∪ [2….4]
3	[2….4]
4	[1] ∪ [3]
5	[1….2] ∪ [5]

The assignment obtained by the D-saturation algorithm is presented below; the frequencies assigned to stations are represented near the summits.

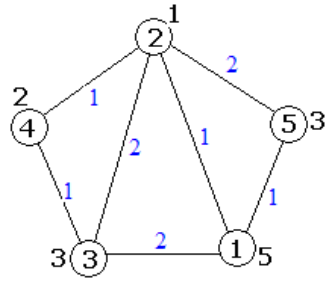


Fig1b: Frequency assignment for our example

At the end of the algorithm, a single bond (Station 1) has been affected by the maximum frequency (5). We could assign it by the frequency strictly lower than 5 which minimizes an objective function F.

We immediately attribute this frequency to this station. This assignment is not a solution to the problem (because the constraints in relation to the altered link will not be respected), it will serve as the basis for the generation of neural network inputs.

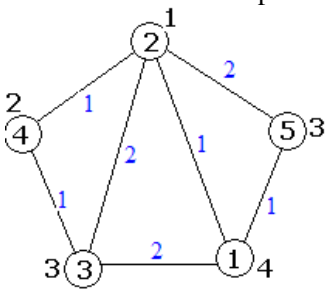


Fig1c: Initial frequency assignment solution

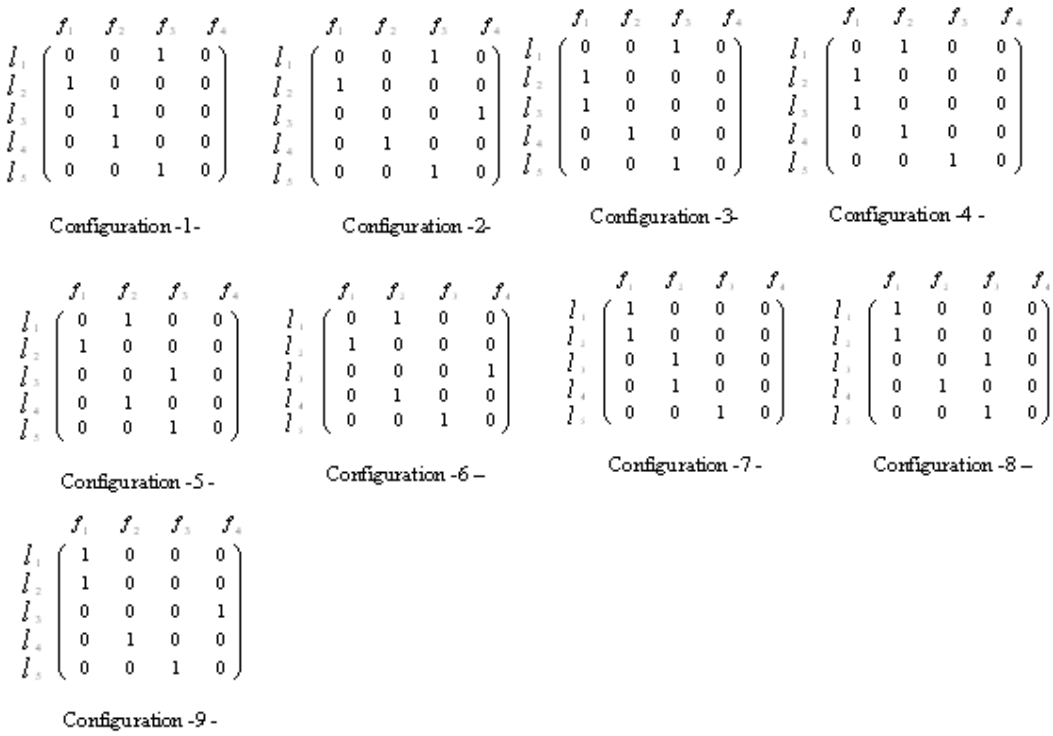
This solution will be represented by a binary matrix:

$$\begin{array}{c} \\ l_1 \\ l_2 \\ l_3 \\ l_4 \\ l_5 \end{array} \begin{array}{c} \begin{array}{cccc} f_1 & f_2 & f_3 & f_4 \end{array} \\ \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \end{array}$$

3. ARTIFICIAL NEURAL NETWORKS AND HIERARCHICAL GENETIC ALGORITHMS

An artificial neural network (ANN) is a mathematical or computational model for information processing based on a connectionist approach to computation. Its global behavior is determined by the connections between the processing elements and element parameters [6].

The processing elements are distributed and strongly connected, with a natural pre-board for memorization and exploitation. Each processing element calculates a single output based on the information it receives. This neuron cell is the basic elementary unit of an ANN. It is built on the digital inputs, through which the environment stimulus arrives. These entries are initialized with a set of configurations (assignments). From the initial allocation for each link Xi visited, we affect the set of frequencies fj different from fi in its spectrum frequency domain. For each touched link we will have a set of fmax-1 configurations.



From each matrix of a configuration, an optimal solution is evaluated to the problem as a linear combination of lines for this one. All obtained solutions, will be used as the entrances to our artificial neural network (ANN) that will be governed by a hierarchical genetic algorithm (HGA). A solution is represented by a vector S such that S = (S1, S2, S3, ..., SM) which constitutes an individual of the AGH.

Each individual consists of a chain of chromosomes C1, C2, C3...CM; where each chromosome is associated to a variable of the problem. The Chromosome Ci ($\forall i \in [1, 2,... ,n]$) corresponds to a variable Xi that is a subdomain (a subset) of D (Xi).

The default entry of the network is called a bias, b, whose weight adjusts the threshold of the neuron activation. Learning in the network is performed as an adaptation process to the simulation results. The network adjusts its internal parameters according to a learning algorithm. It may be necessary to change its structure by creating or deleting neurons. Then the network reacts differently to the environment according to the new experience subsequently gained to the simulation.

In our approach and for the optimization of the parameters and the topology of the ANN, we use an iterative search technique used in conjunction with hierarchical genetic algorithms (HGA), and where the structure of a chromosome is composed of two types of genes:

- Parametric genes representing the actual values of frequencies allocated to bonds in their frequency domain.
- Control genes whose interest is to activate parametric genes. The next scheme gives an example of a phenotype.

Chromosome A: Control genes parametric genes

1	0	1	1	1	4	7	1	3	8

↓

Phenotype CA= (4, 1, 3, 8)

The individual will represent both a subproblem and eventually a solution.

An objective function is associated with each chromosome Ci: $F = [\, f1 , f2 , \ldots , fi \,]^T$

This function corresponds to the number of frequencies used; this information is directly acquired by the control genes.

Chromosome A: Control genes Parametric genes

1	0	1	1	1	4	7	1	3	8

↓

Phenotype CA= (4, 1, 3, 8) fi+1=4

Note that a control gene of the first level is eventually activated by another control gene of the second level, and so on.

The problem is then formulated as a multi-criterion optimization problem F with: $F = \begin{bmatrix} Fi \\ fi+1 \end{bmatrix}$

where $F = [f_1 \quad f_2 \quad .... \quad f_i]^T$

And the function can be used to

- Assess the genetic quality of the chromosomes during the selection of parents;
- And decide whether a chromosome generated by a crossover must replace one of the parents.
- And the subdivision of the population into subgroups of similar complexity.

4. STRUCTURE OF THE HGA-ANN:

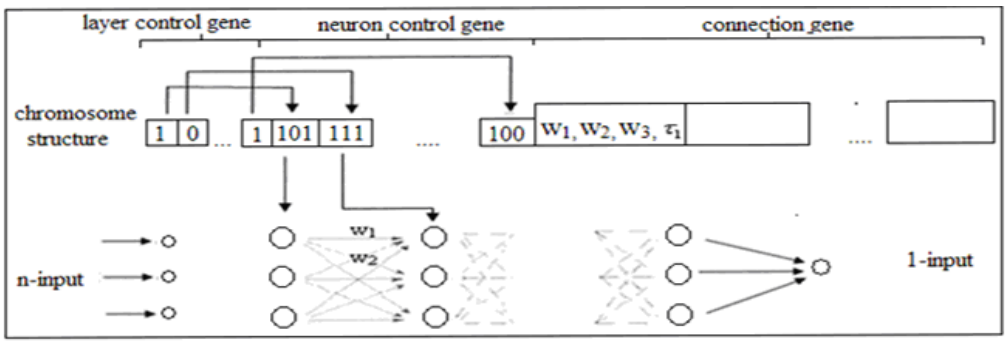


Fig2: Structure of the HGA-ANN [1]

5. POPULATION OF CONNECTIONS OF THE HGA-ANN:

The population of the HGA-ANN at the k^{th} iteration P(k) consists of several sub-groups of connection:

$$G_1^{(k)} \cup G_2^{(k)} \cup \ldots\ldots\ldots \cup G_m^{(k)} = P(k)$$

$$\text{with} \quad G_i^{(k)} \cap G_j^{(k)} = \phi$$

Where m is the maximum number of connections represented by the HGA-ANN, and $G_i^{(k)}$ is the subgroup of chromosomes representing networks with i active connections at the kth generation.

The λ factor is used to define the maximum number of chromosomes in each subgroup of the population, then: size $[G_i^{(k)}] \leq \lambda$. Size$[G_i^{(k)}]$ is the number of elements in $G_i^{(k)}$. Then the maximum number of individuals in the population, Pmax is defined by: Pmax = λ* m During the initialization of the genetic algorithm, there will be P(0) chromosomes to generate P(0) ≤ Pmax.

When a new generation is produced, new chromosomes are inserted into the reproduction basin to explore the next generation of topologies.

To enable the HGA to manage properly these sub-groups, a new insertion strategy of a chromosome C in the population P to the generation (k +1) is proposed:

At generation (k+1)
Step 1 :
if $\{ G_{fi+1}^{(k)}(C) = \phi$ **or size** $[G_{fi+1}^{(k)}(C)] < \lambda \}$ **then**
$\{G_{fi+1}^{(k)}(C) = G_{fi+1}^{(k)}(C) \cup \{C\} < \lambda \}$
else goto step2;
Step 2:
if $\{ F_i(C) < F_m = \max \{ F_i(C), \forall z_j \in G_{fi+1}^{(k)}(C) \}$ **then**
$\{ G_{fi+1}^{(k)}(C) = \{ C_j : F_i(C) < F_m , Cj \in G_{fi+1}^{(k)}(z) \} \cup \{C\} \}$
Else goto step 3
Step 3 : Exit

This regrouping method ensures that chromosomes are only in competition with those of similar complexity (same dimension fi+1). The associated information to the system of topology is not lost even if the other values of F_i are bad. The selection mechanism will focus mainly on the values of F_i.

6. SELECTION AND REPLACEMENT

Generating a new population from the former (or current) is usually based on a fitness function defined on the values of the objective function F of individuals in the population. A better method of ranking based on several criteria may be adopted by the HGA so that the best frequency plan has the rank 1 or each individual Ci has an equal opportunity to be selected, equal to: $tsr = \frac{F - f(C_i)}{(size[P^{(k)}] - 1).F}$ where F is the sum of the fitness values of all the chromosomes of the population P (k).
The rank of chromosome Ci is determined by 1+p if Ci is dominated by p chromosomes of the population P: **rank (C_i) = 1+ p**

- The population is sorted from the objective function F.
- We assign as fitness value to each chromosome C_i: $f(C_i) = f_{\min} + (f_{\max} - f_{\min}) \frac{rank(C_i) - 1}{N_{ind} - 1}$ where f_{min} and f_{max} are the limits of fitness values calculated from F and N_{ind} the number of individuals of population P
- We attribute to individuals of the same rank the average value of these fitness values. Then all individuals of the same rank will have an equal chance of being selected. The fitness function of chromosome Ci will be determined by:

$$f(C_i) = \alpha \, rank\,[f_1(C_i)] + \beta \, f_2(C_i)$$

where α represents the weighting parameter of the ANN. So that β is the weight associated with the complexity of the topology of the ANN. Because the reliability of the ANN is more important than its complexity, we will give special attention to the choice of coefficients α and β .

If we consider that M is the maximum number of active connections in the ANN, then $f_2(C_i) \le M, \quad \forall C_i \in P$ So, there will exist at least one ANN entrained in the population P such as : $f_1(C_i) = 0$ and $rank[f_1(C_i)] = 1$ Then $f_1(C_i) = \alpha + \beta f_2(C_i) \le \alpha + \beta M$ Where $\beta \in R^+$

And if we equally consider that for a chromosome Cj not showing a good learning

$$f(C_j) = \alpha \, rank[f_1(C_j)] + \beta f_2(C_j)$$
$$\ge 2\alpha + \beta f_2(C_j) \quad > 2\alpha$$

α is adjusted such that $\alpha \ge \beta . M$ to ensure $f_1(C_j) > f_2(C_i)$

f_1 is the memorization error for RAN calculated with: $f_1 = \frac{1}{N} \sum_{i=1}^{N} (\bar{y}_i - y_i)^2$

where N is the number of observation-based learning. $\bar{y}_i$ is the output of the network , y_i is the desired output for the i[th] observation vector.

7. REPRODUCTION WITH MUTATION AND CROSSING

The HGA combines the selected individuals through the genetic operators. A mutation operator works by changing randomly one or more genes of a chromosome, while the cross exchanges some genes of a parent with those of another. It may extend to exchange a group of genes called building block.

For each pair of individuals in the breeding population, P, we associate a probability to make the crossing Pc, and the generated individual constitute the population P", whereupon each gene in an individual of P" is transferred by using a genetic search operator before being inserted into the population with a probability Pm. Then Individuals P" represent the new population and the cycle continues with the same sequencing: evaluation, selection, crossover, mutation, ...

For each type of gene (parametric genes and control genes), there will be two genetic operations (crossover and mutation) to be applied. Thus we can consider these operators specified in HGA and this will be considered in a forthcoming publication.

8. RESULTS:

For testing our approach we have used benchmark problems called Philadelphia problems, which have been used widely in previous researches including [8] and [11], these problems are formulated based on an area in Philadelphia, Pennsylvania. The network consists of 21 cells as shown in Figure 3:

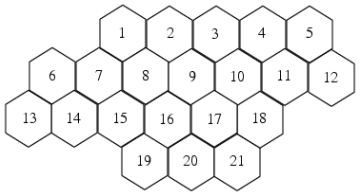


Fig 3 :Cellular Geometry of Philadelphia Problems

Our experiments were conducted on an Intel Pentium M (with 512MB of RAM). There are many variations for setting constraints and demands and several competing teams of researchers have worked on the same instances of problem. We present in Table 1 the parameter setting used in some approaches and adopted by ours evaluations.

In this table,"Nc" means the square of required distance for co-channel constraints, assuming that the distance be-tween adjacent cells is 1. For example, if Nc=12, while cell 1 and cell 5 can use the same frequency (the distance is 4), cell 1 and cell 4 cannot (the distance is 3). "acc" represents the separation required for adjacent channel constraints, and "cii" represents co-site constraints. The demand vectors used in the table are as follows (case 3 and case 4 are obtained by multiplying 2 and 4 to case 1, respectively):

case 1: (8 25 8 8 8 15 18 52 77 28 13 15 31 15 36 57 28 8 10 13 8)
case 2: (5 5 5 8 12 25 30 25 30 40 40 45 20 30 25 15 15 30 20 20 25)
case 3: (16 50 16 16 16 30 36 104 154 56 26 30 62 30 72 114 56 16 20 26 16)
case 4: (32 100 32 32 32 60 72 208 308 112 52 60 124 60 144 228 112 32 40 52 32).

Table 4: Specification for Philadelphia problems

Instance	Nc	Acc	Cii	Demand Vector
P1	12	2	5	Case 1
P2	7	2	5	Case 1
P3	12	2	7	Case 1
P4	7	2	7	Case 1
P5	12	2	5	Case 2
P6	7	2	5	Case 2
P7	12	2	7	Case 2
P8	7	2	7	Case 2
P9	12	2	5	Case 3
P10	12	2	5	Case 4

Table II shows the results obtained with our heuristic. We consider the theoretical lower-bounds as it represented in [8], [9], [10]. and we use the best solution obtained so far. Ours results are compared with results of the best tree methods, from seven reported methods. The tree methods are: First, a constraint satisfaction method (CS) and second a Neural network (NN).the third a Simulated Annealing (SA). The last row in the table shows our results.

Table 5: Comparaison of solution quality

Instance	Lower bounds	CS	NN	SE	RNA-HGA
P1	427	427	427	460	427
P2	427	427	427	447	427
P3	533	533	536	536	533
P4	533	533	533	533	533
P5	258	258	283	283	258
P6	253	253	270	270	253
P7	309	309	310	310	309
P8	309	309	310	310	309
P9	856	856	…	…	856
P10	1714	1714	…	…	1714

To the extent of the authors' knowledge, the best published results for these problems have been obtained by FASoft [9], [10] and [20]. FASoft is an integrated package of various methods for solving frequency assignment problems, such as heuristic sequential methods, methods using constraint satisfaction techniques, Simulated Annealing, GA, tabu search, etc. We show the results obtained with Simulated Annealing (SA) and tabu search (TS) reported in [12]. These two methods are the most efficient among the various components of FASoft. Furthermore, we show the best results obtained with a set of heuristic sequential methods (SE) reported in [10], and the results obtained with neural networks (NN) reported in [20], and the results obtained with a constraint satisfaction method (CS) reported in [14] ("..." in the table means that the result is not reported).
As shown in the table 5, our algorithm obtains optimal solutions for all instances, and obtains exact solutions for other problem instances. Moreover, this method can obtain better or equivalent solutions compared with existing methods for all problem instances.

9. CONCLUSIONS

In this paper we have been interested in the problem of frequency allocation in the context of a dynamic deployment. After having offered an overview and a suitable formulation of the problem we have tried to present a vision for solving the problem and to produce the sequence of optimal frequency plan using an algorithm which is considered as an adaptation of the genetic algorithm by adding a combination of parametric genes combined to an iterative search technique.

The HGA-ANN shows a rapid convergence to optimal solution, and a better optimization of parameters and topology of the neural network. The experimental evaluations using standard benchmark problems showed that for most of the problem instances, this algorithm can find better or equivalent solutions compared with existing optimization methods. And shows more performance efficiency and can achieve self-configuring cellular networks without the need of additional signaling loads and changes to both terminals and base station equipment. It continuously adaptable for a new insertion if a reallocation of radio frequency resources must be made. Furthermore, it is particularly well-suited to this problem and offers distinct advantages compared to existing methods. The HGA-ANN presents a good perspective of managing the radio spectrum that can be directed towards a multi-agent implementation for implementing a relevant strategy and effective management of resources.

ACKNOWLEDGEMENTS

The authors are grateful to all the member of the Laboratory of Electronics and Telecommunications in Mohammadia School of Engineers (EMI) for the contribution of their ideas, and for the contribution of such an approach and who, in one way or another, have helped to improve it.

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