Int. J. Communications, Network and System Sciences, **2011, 4, 727-734**
doi:10.4236/ijcns.2011.411089 Published Online November 2011 (http://www.SciRP.org/journal/ijcns)

Distributed Frequency Assignment Using Hierarchical Cooperative Multi-Agent System*

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Received June 21, 2011; *revised July* 20, 2011; *accepted August* 11, 2011

Abstract

Recent demand for wireless communication continues to grow rapidly as a result of the increasing number of users, the emergence of new user requirements, and the trend to new access technologies. At the same time, the electromagnetic spectrum or frequencies allocated for this purpose are still limited. This makes solving the frequency assignment problem more and more critical. In this paper, a new approach is proposed using self-organizing multi-agent systems to solve distributed dynamic channel-assignment; it concerns distribution among agents which task is to assign personal station to frequencies with respect to well known constraints. Agents only know their variables and the constraints affecting them, and have to negotiate to find a collective solution. The approach is based on a macro-level management taking the form of a hierarchical group of distributed agents in the network and handling all RANs (Regional Radio Access Network) in a localized region regardless of the operating band. The approach defines cooperative self-organization as the process leading the collective to the solution: agents can change the organization by their own decision to improve the state of the system. Our approach has been tested on PHEADEPHIA benchmarks of frequency assignment Problem. The results obtained are equivalent to those of current existing methods with the benefits that our approach shows more efficiency in terms of flexibility and autonomy.

Keywords: Dynamic Frequency Assignment, Optimization Problem, Multi-Agent System, Artificial Intelligence

1. Introduction

With growth in the demand of mobile telephone services, the efficient use of available spectrum is becoming increasingly important. The studies of a frequency assignment problem (also called a channel assignment problem) in cellular mobile systems are so abundant [1-5]. Various Artificial Intelligent (AI) techniques, including constraint satisfaction, simulated annealing, neural networks, taboo search, and genetic algorithms, have been applied to this problem [6-12].

An overview of the frequency assignment problem is as follows: For an existing set of, geographically divided, regions (called cells—typically hexagonal), frequencies (channels) must be assigned to each cell according to the number of call requests. Three types of electro-magnetic separation constraints exist.

- Co-channel constraint: the same frequency cannot be assigned to pairs of the cells that are geographically close to each other.
- Adjacent channel constraint: similar frequencies cannot be simultaneously assigned to adjacent cells.
- Co-site constraint: any pair of frequencies assigned to the same cell must have a certain separation.

The goal is to find a frequency assignment that satisfies the above constraints using a minimum number of frequencies (more precisely, using the minimum span of the frequencies). It must be noted that there exist several variations of frequency assignment problems. The benchmark problems provided by the EUCLID-project Combinatorial Algorithms for Military Applications (CALMA) project are well-known in the constraint satisfaction/optimization research community. This type of problem arises from a military application, and geographical information including cells is not described in the problem specification. Constraint satisfaction/optimization techniques can solve this type of problem quite efficiently.

The objectives of this paper are twofold. First, present

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and formulate the problem of frequency assignment. Second, establish a perspective of resolution based on the application of Hierarchical Multi-Agents System (HMAS) for an intelligent resources management that allows inserting dynamically the new links in the basin of the network.

Unlike centralized conventional methods our approach provides a distributed management framework, which deals with intelligent behavior which is the product of cooperative activity of several agents to fill the limits of classical Artificial Intelligence (AI) for solving this complex problem. Through a passage of individual behavior to collective behavior characterized by a distributed control of distributed among entities (agents) governed by simple rules. Instead of representing each call as a variable, we represent a cell as a variable that has a very large domain. Furthermore, we determine the variable value step by step instead of determining a variable value at one time. To each cell is associated a cooperative agent that handles the assignment of a frequency. Within a Radio Area Network-RAN (Regional Radio Access Network) and at each step, an agent is elected by all its neighbors. The election is based on empirical rules for calculating the degree of separation of an agent, the degree of saturation and the improvement claimed by the neighbors for an assignment. The elected agent assigns the smallest frequency in the spectrum that meets all its constraints. In the case of a non permitted assignment, the agent may be served by a neighboring RAN, through a mechanism of cooperation between supervisor agents of both RANs. If no proposal has been received, the supervisor agent can make a Taboo Search for an improvement in the overall assignment in the associated RAN.

The rest of this paper is organized as follows. In Section II, we review the research contributions in the area frequency assignment. In Section III, we formulate the frequency assignment problem. In Section IV, we describe our resolution approach to this problem that utilizes hierarchical multi-agent system. Section V is reserved to show experimental evaluations using standard benchmark. Finally, Section VI concludes our work with a comparison to other current research and a projection for future issues.

2. Related Work

The current challenges in radio networks are: to ensure an efficient and full use of radio frequency resources and multimedia applications, Connect at best anywhere, anytime and with any network. Customize the more powerful features stimulated by the increasing consumers' demand. Find solutions for the mobile business. And tend toward several access technologies whose assignment is local and continuously and independently updated, rendering impossible any overall control. This lead to a very interesting and pertinent issue for radio spectrum is dynamic spectrum assignment problem.

This problem is one of the most studied problems in the literature, particularly multiple variants algorithms are proposed for solving this problem [1,5,7,10,11,13-16].

The problem starts from some networks initial connections (namely robust) to develop progressively the subsequent connections according to the operational change of 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 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, and 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-coloring problem [7]. However, solving real-life, large-scale problems' using this simple formulation seems rather difficult without avoiding the symmetries between calls within one cell [2].

Unlike greedy methods, meta-heuristics seek to find 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.

The simulated annealing technique (SA) is a stochastic computational technique used for solving big optimization problem such as frequency assignment problem, by determining the global minimum value of an objective function with various degrees of freedom subject to the problem in a reasonable amount of time. This technique is more efficient than the Taboo search technique; its advantages are its generality and 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 [6].

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. 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. 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 [17].

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 [1]; 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 [17]. But the Genetic algorithms are expensive in computing time, as they handle multiple solutions simultaneously.

3. Frequency Assignment Problem Formulation

A frequency assignment problem can be formalized as follows:

Let $T = \{t_1, t_2, \cdots, t_n\}$ be a set of n transceivers (TRXs), and let $F_i = \{f_{i_1}, f_{i_2}, \cdots, f_{i_k}\} \subset N$ be the set of valid frequencies that can be assigned to a transceiver $t_i \in T$, $i = 1, \cdots, n$ (the cardinality of Fi could be different to each TRX). Furthermore, let $S = \{S_1, S_2, \cdots, S_m\}$ be a set of given sectors (or cells) of cardinality m. Each transceiver $t_i \in T$ is installed in exactly one of the m sectors and is denoted as $S(t_i) \in S$.

The set of constraints is represented by a m*m matrix called matrix of compatibility: $M = \{(\mu_i, \sigma_i)\}_{m*m}$. The two elements μ_{ij} and σ_{ij} of a matrix entry $M(i, j) = (\mu_{ij}, \sigma_{ij})$ are numerical values greater than or equal to zero and they represent the mean and standard deviation respectively, of a Gaussian probability distribution used to quantify the interferences ratio (C/I) when sector i and j operate on a same frequency. Therefore, the higher the mean value is, the lower interferences are, and thus it will have a superior communication quality.

A solution to the problem lies in assigning to all the TRXs (t_i) a valid frequency from its domain (F_i), in order to minimize the following cost function:

$$C(p) = \sum_{t \in T} \sum_{u \in T, u \neq t} C_{sig}(p, t, u) \qquad (1)$$

where C_{sig} will compute the co-channel interferences (C_{co}) and the adjacent-channel interferences (C_{adj}) for all sector t and u, in which the transceivers t and u are installed, that is, $s(t)$ and $s(u)$, respectively.

$p \in F_1 \times F_2 \times \cdots \times F_n$ denotes a solution (or frequency plan), where $p(t_i) \in F_i$ is the frequency assigned to the transceiver t_i. Moreover, $\mu_{s_t s_u}$ and $\sigma_{s_t s_u}$ are the interference matrix values at the entry $M(s_t, s_u)$ for the sectors s_t and s_u. In order to obtain the C_{sig} cost from Equation (1), the following conditions are considered:

$$\begin{cases} K & \text{if } s_t = s_u, |p(t) - p(u)| < 2 \\ C_{co}(\mu_{s_t s_u}, \sigma_{s_t s_u}) & \text{if } s_t \neq s_u, \mu_{s_t s_u} > 0, |p(t) - p(u)| = 0 \\ C_{adj}(\mu_{s_t s_u}, \sigma_{s_t s_u}) & \text{if } s_t \neq s_u, \mu_{s_t s_u} > 0, |p(t) - p(u)| = 2 \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

where K, being a very large value, is defined in the configuration file of the network. The K value makes it undesirable to allocate the same or adjacent frequencies to TRXs that are installed in the same sector. In our approach to solve this problem, this restriction was incorporated in the creation of the new solution (frequency plan) produced by the algorithm. Therefore, we assure that the solution does not have this severe penalty, which causes the most undesirable interferences as shown in [1] and [3].

4. Resolution Approach and Development

The approach comes in the form of a group of distributed agents in the network where each regional network is overseen by a supervisor agent. That it combines an agent to each cell called a station agent.

4.1. Station Agent

An agent can be defined as a computer system located in an environment and which can act autonomously and flexibly to achieve the objectives for which it was designed [12].

To each link l_i is associated an agent Ai responsible of assigning a value f_i in its domain D_i.

Two data are sufficient to characterize the agent outside its environment:

First, the frequency value of the corresponding link: The agent chooses among the values in the frequency domain corresponding to this link: for each A_i in A, the $f_i \in D_i$, where D_i is the frequency domain of l_i.

Second, the difficulty of an agent defined as a quantitative measure that reflects the current status of this agent. It is the decision criterion used to choose an agent. It is represented in the form of two essential and sufficient entities that are the degree of separation and the degree of saturation, and it is the criterion used to select the elected agent.

These two entities are intuitively and experimentally determined.

For any agent $A_i \in A$, we note $D(A_i)$ the degree of separation of the corresponding link l_i as the sum of the incident constraints values to stations.

For each A_i in A, $D(A_i) = \left\{ \sum_{i \neq j} C_{ij} \text{ where } C_{ij} \in C \right\}$.

The degree of saturation at step p is determined from the banned intervals for those links that are not yet assigned. It can be deduced by the number of unsatisfied constraints.

For $A_i \in A$, NIS(A_i) is the number of unsatisfied constraints with its value f_i:

$$NIS(A_i) = \left\{ \sum_{i \neq j} C_{ij}, \text{ for each } A_j \text{ such as } f_j \neq 0 \text{ and } C_{ij} \neq 0 \right\}.$$

At step p and for each A_i in A, D_SATp(A_i) = NIS(A_i)

The agent who has the greatest degree of saturation will be considered as the most on difficulty.

Each agent operates in a physical environment; it is its frequency domain. Even though these domains may be identical between several agents, these domains are not shared.

Similarly an agent has an unshared copy of constraints that allows it to be independent of other agents.

The social Environment consists of all neighbors of an agent from which it has only a partial view. It knows about its neighbors only their values and their difficulties. It has no idea about its neighbors' constraints, views, and domains. The communication is performed by sending messages and a mailbox is associated with each agent that stores the received messages from other agents [18].

The neighborhood of an agent Ai is defined by all agents connected by a constraint to this agent.

For each A_i in A, $V(A_i) = \left\{ A_j \in A / C_{ij} \neq 0,\ C_{ij} \in C \right\}$.

Any change of view leads to an immediate update of the state of constraints. The agent will be in a consistent state at any time.

Behavior:

The behavior of an agent takes place in three phases:

One the one time and through the communication mechanism between the agent and its neighbors that is supposedly in place and robust, conducted by messages, where each message reaches in a finite time. And that each agent always handles the messages it receives, the agent manages to know the degree of saturation and values of agents in its neighborhood. Then decide if it moves or not. At the end of a movement, the corresponding environment is maintained.

The agent is autonomous, homogeneous in its behavior than its performance with those neighbors. Consistency between the view of the agent and its local constraints is permanent. Any change of view leads to an immediate update of the state of constraints.

Thus an agent will be able to calculate the degree of saturation as soon as he knows the value of the agents in its neighborhood. These conditions are not blocking the measure in which agents communicate their information once they have them.

Note here that, through cooperation, the random does not play a role as might be the case for other methods. This is not to randomly select an agent to explore more options. But rather to select an agent from among those agents considered equals which all lead to a good solution. So the agent with the greatest difficulty will try to improve its situation since he was elected. This phase marks one of the aspects of cooperation: agents let act the agent the greatest difficulty if it isn't the elected.

The next phase is only possible for an agent elected at the previous phase. The elected agent will select and assign a value that considers the best for him and his neighbors from his private domain of values. And one that minimizes the sum of local cost constraints, based on its current information.

At the end of this phase, the agent deactivates: he reported to his neighborhood and his supervisor that he will not participate in the next election as one of its neighbors have not been elected. This egalitarian policy for the election allows any neighbor with the less difficulty to have the opportunity to be elected. While it is disabled, if one of its neighbors is elected, the agent is still invited to the assignment session: such deactivation is a result of the last phase.

Once booted, the agents will carry out the cycle (election, decision and assignment) but they can not finish themselves. It is the supervisor agent who will take over this task when the execution time limit is reached or a termination criterion is achieved: an overall objective corresponding to the results already known for this problem [19].

The behavior of an agent can be presented as follows:

Step 1:

//determine all of these neighbors

Determine $V(A_i)$;

$V(A_i) = \{A_j \in A\ (j \neq i) / C_{ij} \neq 0\}$

//calculate its degree of separation for an agent

Calculate $D(A_i)$;

For all $A_j \in V(A_i)$ $(j \neq i)$

A_i sends $D(A_i)$ to A_j;

A_i Receives $D(A_j)$;

End For

//if the Agent A_i is the largest $D(A_i)$ then it is the elected

If { $\forall A_j \in V(A_i)$, $D(A_i) > D(A_j)$ }

Then A_i is elected;

A_i: $f_i \leftarrow f$ such as

f = min {f_i, $\forall f_i \in D_i / \forall A_j \in V(A_i)$ such as $f_j \neq 0$ and $|f_i - f_j| > C_{ij}$ (C_{ij} is true)};
//affects the frequency f, D_i the A_i frequency Domain
A_i sends f_i to all $A_j \in V(A_i)$;
A_i deactivates;
go to step 3;
Else
Receives f_j
//receives the frequency of the elected agent
go to step 2;
End If
Step 2:
Calculate D_SATp(A_i)
//the degree of saturation on step p
For all $A_j \in V(A_i)$ such as $f_i = 0$ ($j \neq i$):do
A_i sends D_SATp(A_i) to A_j;
A_i receives D_SATp(A_j) ;
End For
If {$\exists A_j \in V(A_i)$/D_SATp(A_j) > D_SATp(A_i) }
Then Go to Step 2;
Else If {$\exists A_j \in V(A_i)$ /D_SATp(A_j) = D_SATp(A_i)}
If {$D(A_i) > D(A_j)$ } then A_i is elected ;
A_i: $f_i \leftarrow f$ such as
f = min {f_i, $\forall f_i \in D_i / \forall A_j \in V(A_i)$ such as $f_j \neq 0$ and $|f_i - f_j| > C_{ij}$ (C_{ij} is true)};
//affects the frequency f_i, D_i the A_i frequency Domain
A_i sends f_i to all $A_j \in V(A_i)$;
A_i deactivates;
go to step 3;
Else
Go to Step 2;
End If
End If
Else
A_j is elected;
A_i: $f_i \leftarrow f$ such as
f = min {f_i, $\forall f_i \in D_i / \forall A_j \in V(A_i)$ such as $f_j \neq 0$ and $|f_i - f_j| > C_{ij}$ (C_{ij} is true)};
//affects the frequency f, D_i the A_i frequency Domain
A_i sends f_i to all $A_j \in V(A_i)$;
A_i deactivates;
go to step 3;
End If
Step 3:
//Elimination of the agent
Exit;

4.2. Supervisor Agent

The supervisor agent is first in charge of the cooperation between other neighbors RANs supervisor agents. Second, the supervisor agent oversees the management of assignments by:

- Initializing agents associated to stations: called station agents.
- Sending all RAN data associated to station agents: associated Frequency Domain, re-use matrix, stations rentals.
- Holding and collecting responses (until triggering a timeout). In case of a non permitted assignment within its RAN, the agent may resort to another supervisor agent.

The supervisor agent can communicate with other resources outside of its frequency domain through a cooperation procedure similar to all supervisor agents of various RANs.

In the case of a blockage, a Taboo search is performed on the overall allocation to achieve an optimal allocation of all stations of the associated RAN.
This part will be considered in details in our forthcoming publications.

5. Results

We have tested our approach of hierarchical multi agents System (HMAS) simulated at a RAN level for the frequency assignment problem (FAP), such as it is modeled on the web page of the site of the Research Institute of Zuse Institute Berlin ZIB dedicated to an area on Philadelphia-Pennsylvania (http://fap.zib.de/problems/Philadelphia/ and in [20]), which have been used widely in previous researches including [1,14,15].

These problems are formulated based on an area in Philadelphia, Pennsylvania. The network consists of 21 cells as shown in **Figure 1**.

Our experiments were conducted on an Intel Pentium Inside (with 4 GB 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.

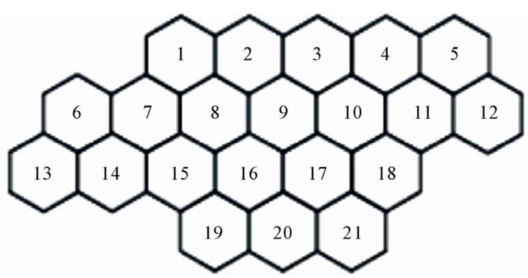

Figure 1. Cellular geometry of philadelphia problems.

Table 1. Specification for philadelphia problems.

Instance	N_c	acc	C_{ii}	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 2. Comparaison of solution quality.

Instance	Lower bounds	CS	NN	SE	HMAS
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

In this table, "N_c" means the square of required distance for co-channel constraints, assuming that the distance between adjacent cells is 1. For example, if $N_c = 12$, 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 "C_{ii}" 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 2 shows the results obtained with our approach. We consider the theoretical lower-bounds as it represented in [1,5,20], 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.

To the extent of the authors' knowledge, the best published results for these problems have been obtained by FASoft [1,9,15,20]. 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 [9]. 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 [5], and the results obtained with neural networks (NN) reported in [6], and the results obtained with a constraint satisfaction method (CS) reported in [1] ("..." in the table means that the result is not reported).

As shown in the **Table 2**, our algorithm obtains optimal solutions for all instances. Moreover, this method can obtain better or equivalent solutions compared with existing methods for all problem instances,

To examine the efficiency of the proposed algorithm in larger-scale problems, we show the evaluation results for the benchmark problems presented in [15,19]. There are 7*7 symmetrically placed cells (49 cells in all) in these problems. Problem parameters are described in **Table 3**, where "C_{ij}" is the minimal frequency separation between any pair of cells whose distance is less than $\sqrt{N_c}$, except for adjacent cells. The demand vector is: (19 14 11 13 15 23 21 25 19 20 21 17 10 18 27 23 29 10 17 16 22 14 19 14 22 27 28 25 30 14 18 28 26 12 10 27 29 11 18 24 24 20 25 12 22 25 29 19 14). This vector is randomly generated from a uniform distribution between 10 and 30. There are 976 calls in total. **Table 4** shows the results obtained with our new method (hybrid Taboo search). For comparison, we show the results described in [15], *i.e.*, the results obtained using neural networks (NN), and the best results obtained with a constraint satisfaction method (CS).

Since the optimality of the obtained solution is guaranteed, and the execution time for these instances is very short, our approach obtains much better solutions than those of NN and CS for all instances and a very high-quality solutions are obtained within a reasonably short running time.

Table 3. Specification for Kim's benchmark problems.

Instance	N_c	C_{ij}	acc	C_{ii}
K1	7	1	1	3
K2	7	2	3	5
K3	7	3	4	7

Table 4. Comparison of solution quality.

Instance	CS	NN	SE	HMAS
K1	168	168	178	164
K2	422	435	473	408
K3	619	630	673	594

6. Conclusions and Future Issues

In this algorithm, we represent a link as a variable with a very large domain, and determine the variable value dynamically and step by step. Which is handled by a computer system located in the environment and can act autonomously and flexibly to achieve the objectives for which it was designed. Furthermore, we have developed a powerful cell-ordering heuristic and introduced the limited discrepancy search to cope with large-scale problems.

Experimental evaluations using real standard benchmark problems showed that for most of the problem instances, our approach can find better or equivalent solutions compared with existing current optimization methods. These results imply that paradigm of distributed agents is capable of solving realistic application problems, if we choose the appropriate problem representation, and provides a conceptual framework for modeling and simulating a complex system.

Furthermore, it is particularly well-suited to this problem and offers distinct advantages compared to existing methods. It incorporates an extra macro-level management and handling all RANs in a localized region regardless of the operating band, where each regional network is overseen by a supervisor. It shows more efficiency in terms of flexibility and autonomy. It is continuously adaptable for a new insertion if a reallocation of radio frequency resources must be made. Since the system can be added to, modified and reconstructed, without the need for detailed rewriting of the application. This system also tends to be rapidly self-recovering and failure proof, usually due to the heavy redundancy of components and the self managed features. We can say that our approach is justified by: Adapting to reality, cooperation, the integration of expertise incomplete, modularity, effectiveness and reliability. Our future works also include evolutionary multi-agent algorithms that are stronger, introducing the hybrid genetic algorithms with iterative improvement of search.

7. Acknowledgements

The authors are grateful to all members 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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