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Comparative Study of Particle Swarm Optimization and Genetic Algorithm for the Migration from an Existing Network to a New Generation Network

Raphaël NLEND
PhD Research Scholar
Department of Electrical and Telecommunications Engineering
National Advanced School Polytechnic,
University of Yaoundé 1, Cameroon

Emmanuel TONYE
Professor
Department of Electrical and Telecommunications Engineering
National Advanced School Polytechnic,
University of Yaoundé 1, Cameroon

Abstract:- In this paper we model the problem of base station migration as an optimization issue by the use of particle swarm algorithm in order to minimize a target goal which is a weighted function of network coverage, traffic, energy consumption and the cost of infrastructure. We then compare the results with those obtained by applying the genetic algorithm under the same conditions. Overall, genetic algorithms are more efficient than particle swarms for the network migration problem.

Keywords:- *Cellular network planning, Genetic Algorithm, Particle swarm optimisation.*

I. INTRODUCTION

In wireless networks, Base station (BS) optimal positioning is a fundamental issue as it represents a significant investment for operators in terms of installation costs and energy consumption [1]. It is also a guarantee for network coverage, quality of service and user experience. Faced with this situation, the optimization of BS positioning becomes a major challenge to enable the reduction of investment and operating costs while improving the quality of service provided to users.

With increasing demand from users for throughput and quality of service, mobile network operators are migrating from a given network to a higher-performance next-generation network. To comply with cost reduction objectives, the capitalization of existing infrastructure is a desired option.

However, combining the existing and new infrastructures out of an appropriate approach can hamper the quality of the service provided to users, since the cell ranges of the new generation networks generally provides a smaller coverage radius than those of previous generation networks. In our previous article [24] we have shown that this NP-Complete problem has received less attention in literature and we have proposed a method based on genetic algorithm for solving it. Given that particle swarm optimization algorithm is a promising optimization method, it is therefore possible to ask the question, which is the most efficient methods between genetic algorithms and particle swarms? The answer to this question for solving the problem of the migration from a given cellular network to a new generation network constitutes the main theme of this article. The rest of the article is structured as follows: Section 2 presents the literature review, Sections 3 formulates the problem and presents the methodology used, Section 4 presents the pseudo code, Section 5 presents the results and comments.

II. LITERATURE REVIEW

Several works have been proposed in literature to study the deployment of BS. These studies tried to model the optimal placement of BS in a given area of interest using genetic algorithms [1] - [10].

Other works have been done to model the optimization of wireless network planning by particle swarms. A new method of planning 4G cellular networks is proposed in [11]. This approach is based on swarm intelligence (particle swarm optimization and Grey wolf optimizer) to satisfy both coverage and capacity constraints in an area of interest consisting of several sub-areas of different spatial densities. In [12], the authors propose a new algorithm based on particle swarm optimization to solve the problem of the optimal positioning of Controllers in a wireless network. In this approach, the authors seek to minimize the sum of the distances of a controller and associated BS while ensuring compliance with capacity constraints. In [13] authors study the problem of allocating resources in a Femto Cell in order to maximize its throughput while reducing interference with neighboring cells. In this perspective, a difficult problem of joint optimization of signal power and channel allocation is formulated followed by its optimization using the particle swarm algorithm. The authors in [14] propose a new method based on particle swarm optimization to solve the problem of maximum coverage in a cellular network. All these studies consider areas of interest without any existing infrastructure. In this article, we are going to tackle the problem of migrating from an existing network to a new generation network by reusing the existing infrastructure with the aid of Genetic algorithm and particle swarm optimization.

III. RESOLUTION APPROACH BY GENETIC ALGORITHMS (GA) AND PARTICLE SWARM OPTIMIZATION (PSO)

In this model, we address the problem of optimally placing new sites combined with existing sites within the framework of migrating from a current network to a new cellular network. This placement must ensure the coverage of the area of interest, the satisfaction of the demand for user's traffic while reducing the number of sites and the amount of energy used.

For this to be done, we consider an area of interest $V = \{1, \ldots\ldots, n\}$, a set of $I = \{1, \ldots\ldots, N_b\}$ of a given configuration of base stations and a set of client location $J = \{1, \ldots\ldots, l\}$. The set I contains a number n_{fixe} of existing sites with locations known and n_{new} new sites arbitrarily placed so that $N_b = n_{fixe} + n_{new}$.

The rest of the formulation is described in the same way as in [24] section 3.

A. *Representation of the population*

$$B = \{(x_1, y_1, p_1, r_1, e_1), \ldots\ldots, (x_{n_{fixe}}, y_{n_{fixe}}, p_{n_{fixe}}, r_{n_{fixe}}, e_{n_{fixe}}),$$
$$(x_{n_{fixe}+1}, y_{n_{fixe}+1}, p_{n_{fixe}+1}, r_{n_{fixe}+1}, e_{n_{fixe}+1}), \ldots\ldots, (x_{N_b}, y_{N_b}, p_{N_b}, r_{N_b}, e_{N_b})\}$$

A configuration of users is given by:

$$U = \{(X_1, Y_1, d_1), \ldots\ldots, (X_u, Y_u, d_u), \ldots\ldots, (X_l, Y_l, d_l)\}$$

X_i : *abscissa of user i*

Y_i : *ordinate of user i*

d_i : *traffic demand of user i*

➢ *Case of genetic algorithms.*

Genetic algorithms are research and optimization methods based on the principles of natural selection and genetics. Some principles of genetics are borrowed and used artificially to formulate robust algorithms. The genetic algorithms are inspired by Darwin's theory of evolution "survival of the fittest" which suggests that in a competition of individuals for scarce resources, the most able individuals outweigh the weakest [17].

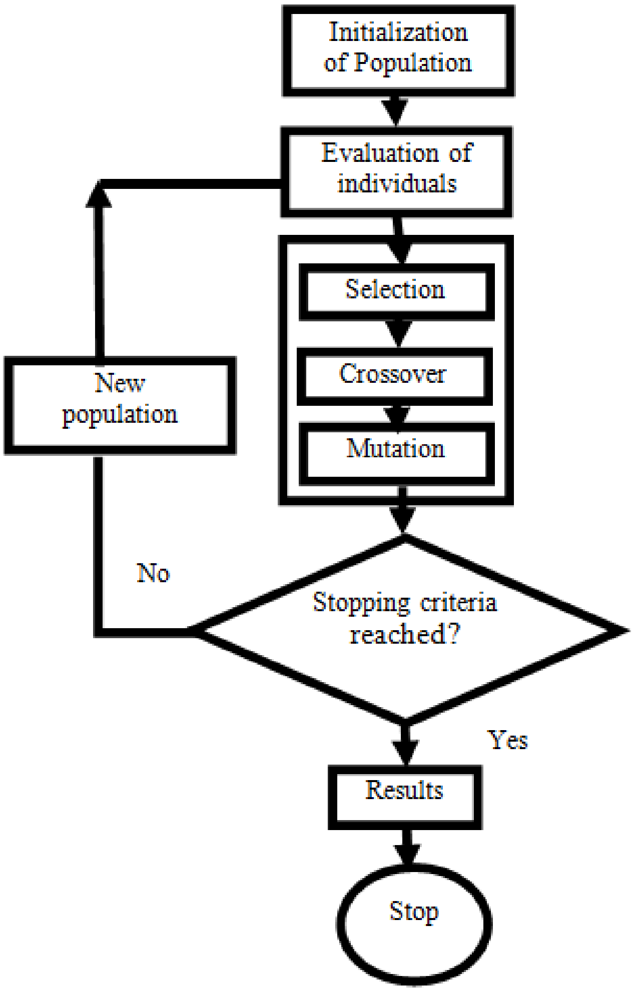

Fig. 1 :- Flow chart of the genetic algorithm [18]

* *Representatation of the population at the K^th step*

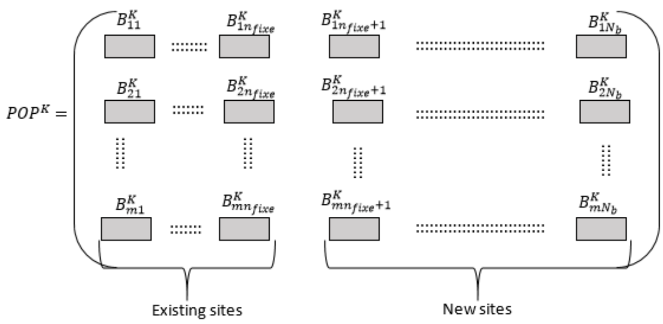

Fig. 2 :- Representation of the population at the K^th generation

It should be noted that for each column $j\left(1 \le j \le n_{fixe}\right)$, $\left(B^k_{ij}\right)$ has the same value for $\left(1 \le i \le m\right)$.

* *Genetic operators and Stopping criteria*

The selection, crossover and mutation operators as well as the stopping criteria are defined as in [24] section 5.

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➢ *Case of Particle swarm*

Particle swarm optimization is a global optimization method that has nuances to genetic algorithms. In the same way as Genetic Algorithms, a population of potential solutions is used to scrutinize the search space, but no operator, inspired by evolutionary algorithms, is used to search for new promising solutions. On the other hand, in the particle swarm optimization, the swarm adjusts its trajectory according to its current speed, its best position and the best known position in its neighbourhood. [19] [20].

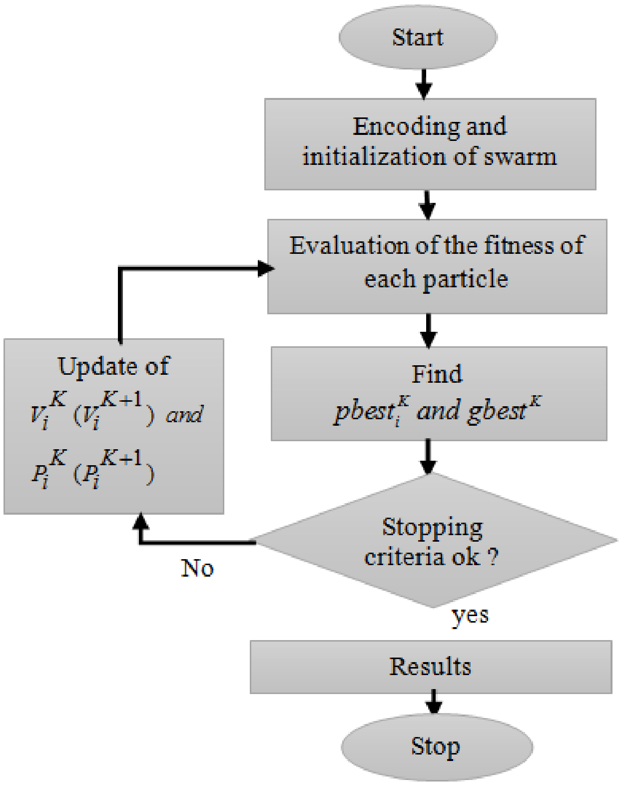

Fig. 3:- Flow chart of the optimisation by Particle swarms [21]

- *Representatation of the swarm at the K^{th} step*

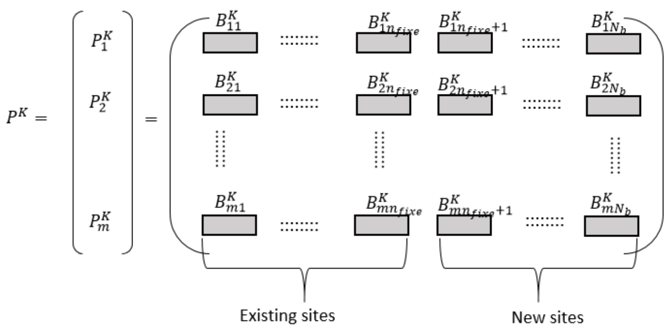

Fig. 4. Representation of the swarm at the K^{th} step

It should be noted that for each column $j\left(1 \le j \le n_{fixe}\right)$, $\left(B_{i\,j}^{k}\right)$ has the same value for $\left(1 \le i \le m\right)$.

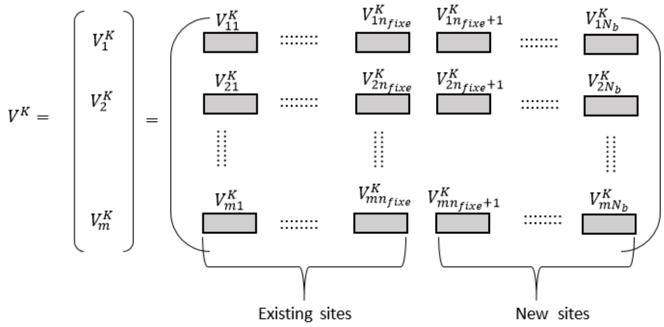

Fig. 5 :- Representation of the swarm velocities at the K^{th} step

It should be noted that for each column

$$j\left(1 \le j \le n_{fixe}\right),\ V_{i\,j}^{k} = 0,\ for\ 1 \le i \le m \qquad (1)$$

- *Particle velocity and position calculation [22]*

$$V_{ij}^{K+1} = w * V_{ij}^{K} + c_1 * r_1 (pbest_{ij}^{K} - P_{ij}^{K}) + c_2 * r_2 (gbest_{j}^{K} - P_{ij}^{K}) \qquad (2)$$

$$P_{ij}^{K+1} = P_{ij}^{K} + V_{ij}^{K+1} \qquad (3)$$

P_{ij}^{K} is the component j of the particle i at the K^{th} step

V_{ij}^{K+1} is the component j of the velocity of the particle i at the K^{th} step

$pbest_{ij}^{K}$ is the component j of the best position through which the particle i has passed from the start of the process up to the K^{th} step

w is the inertia factor, c_1 is the cognitive component and c_2 is the social component

r_1 and r_2 are positive numbers that maintain the diversity

➢ *Objective function applicable to both genetic algorithm and particle swarm optimization [24]*

$$f(G) = Min\left[w_c f_c(G) + w_t f_t(G) + w_e f_e(G) + w_p f_p(G) \right] \qquad (4)$$

$$f(G) = Min\left[\begin{array}{l} w_c * \dfrac{A_T - \sum_{s=1}^{N_b} A_s * e_s}{A_T} + w_t * \dfrac{U_T - \sum_{s=1}^{N_b} U_s * e_s}{U_T} \\ + w_e * \dfrac{\sum_{s=1}^{N_b} e_s}{N_b} + w_p * \dfrac{\sum_{s=1}^{N_b} p_s * e_s}{N_0 * p_{max}} \end{array} \right]$$

$$w_c + w_t + w_e + w_p = 1 \qquad (5)$$

➢ *Area of interest*

The area of interest used in our study is a simulation of the mapping of the city of Yaoundé with an area of 183 km^2 or 13.53 km x 13.53 km. This space is represented in Cartesian coordinates by abscissas varying in the range [1 to 14.53] and the ordinates varying in the range [2 to 15.53]. The sizing done in [23] shows that 244 sites are needed in the area. To take into account the recovery of the cells by 20%, we will multiply the previous number of sites by 1.20 to obtain 293 sites. We assume that our area has 100 existing sites and n_{new} sites to complete among the 193 random sites.

IV. PSEUDO CODE

A. Case of genetic algorithm

The Pseudo coding of the optimization by the genetic algorithms is the same as indicated in article [24] section 7.

B. Case of particle swarms

Initialize the vector of the n_{fixe} existing sites, v_{fixe}

Initialize the swarm of n_{new} random sites, P_{new} ensuring that new sites do not coincide with existing ones.

Initialize the velocities of the existing sites to 0 and those of the swarm Initialize $pbest_i^K$ *and* $gbest^K$ Evaluate each particle (P_{new}) merged with v_{fixe}

While stopping condition is not reached

Update the velocities of each particle in the swarm $V_i^K\ (V_i^{K+1})$ *and* $P_i^K\ (P_i^{K+1})$

Evaluate each particle merged swarm with v_{fixe} Find the best positions of each particle and the best position of the swarm $pbest_i^{K+1}$ *and* $gbest^{K+1}$

End While
End.

V. RESULTS AND COMMENTS

The simulation results have been obtained by using MATLAB version R2018a

A. Simulation parameters

➢ *System Parameters*

The system parameters are defined as in [23]

➢ *Genetic algorithm parameters*

The parameters of the genetic algorithm are defined in the same way as those in section 8 of [24]

➢ *Parameters of Particle Swarm Optimization Algorithm*

Parameter	*Value*
A_T (km^2)	180 (13.41x13.41)
U_T	1000
n_{fixe}	100
n_{new}	193
$x_{\min}$	1
$x_{\max}$	14.53
$y_{\min}$	2
$y_{\max}$	15.53
$p_{\min}$ (dB)	43
$p_{\max}$ (dB)	46
$e_{\min}$	0
$e_{\max}$	1
Number of particles	100
c_1	2
c_2	2

Table 1:- Parameters of Particle Swarm Optimization Algorithm

It should be noted that particle velocities are bounded as follows:

$$V_{x_{\max}} = 0.1*(x_{\max} - x_{\min}) \quad (6)$$
$$V_{x_{\min}} = -V_{x_{\max}} \quad (7)$$
$$V_{y_{\max}} = 0.1*(y_{\max} - y_{\min}) \quad (8)$$
$$V_{y_{\min}} = -V_{y_{\max}} \quad (9)$$
$$V_{p_{\max}} = 0.1*(p_{\max} - p_{\min}) \quad (10)$$
$$V_{p_{\min}} = -V_{p_{\max}} \quad (11)$$
$$V_{e_{\max}} = 0.1 \quad (12)$$
$$V_{e_{\min}} = -0.1 \quad (13)$$

The inertia is given by:

$$w = 1*(0.9)^n \quad (14)$$

n *is the step number*

❖ *Results*

Considering:

The coverage rate:

$$f_C^{'}(G) = 1 - f_C(G) \quad (15)$$

The rate of reduction of energy consumption:

$$f_p'(G)=1-f_p(G) \quad (16)$$

The rate of reduction of the number of sites:

$$f_e'(G)=1-f_e(G) \quad (17)$$

The users connected rate:

$$f_t'(G)=1-f_t(G) \quad (18)$$

- *Table comparing the results of the genetic algorithm and particle swarms optimisation*

Situation (a) : Common weights, $w_c = 0.4; w_t = 0.3; w_p = 0.2; w_e = 0.1;$ *Common number of iterations : 20000;*
Number of particles : 100 (PSO); Number of individuals : 100; mutation: one point (AG)

AG							PSO				
Selection Type	Cross-over type	$f_c'(G)$ in %	$f_p'(G)$ in %	$f_e'(G)$ in %	$f_t'(G)$ in %	$f(G)$	$f_c'(G)$ in %	$f_p'(G)$ in %	$f_e'(G)$ in %	$f_t'(G)$ in %	$f(G)$
Rou -lette	One point	80.88	2.66	40.95	99.8	0.33	75.20	2.96	45.73	95.1	0.36
	Two point	78.44	2.78	43.00	99.8	0.33	75.20	2.96	45.73	95.1	0.36
Tourna-ment	One point	81.16	2.66	40.27	100%	0.32	75.20	2.96	45.73	95.1	0.36
	Two point	80.43	2.51	41.63	99.9	0.33	75.20	2.96	45.73	95.1	0.36
Random	One point	80.78	2.80	40.27	99.9	0.33	75.20	2.96	45.73	95.1	0.36
	Two point	82.59	2.44	39.59	99.9	0.32	75.20	2.96	45.73	95.1	0.36

Table 2:- Comparison of GA and PSO results for the situation (a)

Situation (b) : Common weights, $w_c = 0.3; w_t = 0.2; w_p = 0.3; w_e = 0.2;$ *Common number of iterations : 20000;*
Number of particles : 100 (PSO); Number of individuals : 100; mutation: one point (AG)

AG							PSO				
Selection Type	Cross-over type	$f_c'(G)$ in %	$f_p'(G)$ in %	$f_e'(G)$ in %	$f_t'(G)$ in %	$f(G)$	$f_c'(G)$ in %	$f_p'(G)$ in %	$f_e'(G)$ in %	$f_t'(G)$ in %	$f(G)$
Rou -lette	One point	80.91	2.55	41.29	99.9	0.46	71.35	3.14	48.46	94.3	0.49
	Two point	79.37	2.35	43.68	99.8	0.46	71.35	3.14	48.46	94.3	0.49
Tourna-ment	One point	79.92	2.37	43.00	100	0.46	71.35	3.14	48.46	94.3	0.49
	Two point	77.67	2.53	44.36	100	0.47	71.35	3.14	48.46	94.3	0.49
Random	One point	81.45	2.41	41.29	99.9	0.46	71.35	3.14	48.46	94.3	0.49
	Two point	79.59	2.70	42.66	99.9	0.46	71.35	3.14	48.46	94.3	0.49

Table 3:- Comparison of GA and PSO results for the situation (b)

a) Graphic representation of the results

for $w_c = 0.4; w_t = 0.3; w_p = 0.2; w_e = 0.1$; *number of individuals*:100
Number of iterations :20000; *mutation*: *one point*; *Selection by roulette*
– **genetic algorithm**

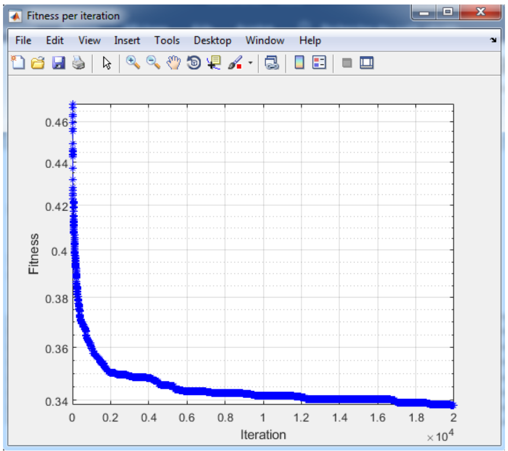

Fig. 6:- Evolution of the fitness according to the number of iterations

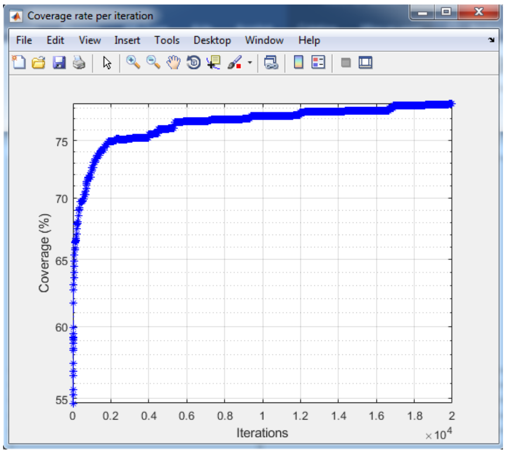

Fig. 7:- Evolution of the coverage rate according to the number of iterations

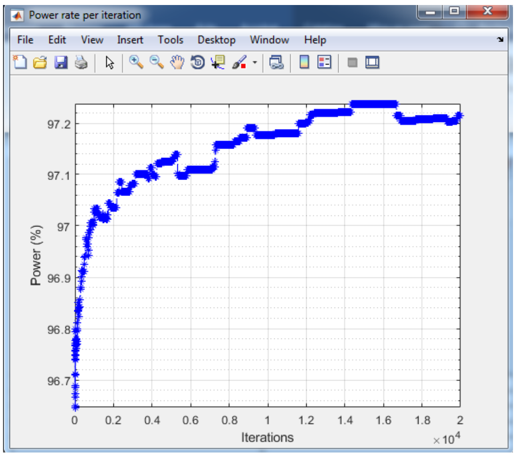

Fig. 8:- Evolution of the power used rate according to the number of iterations

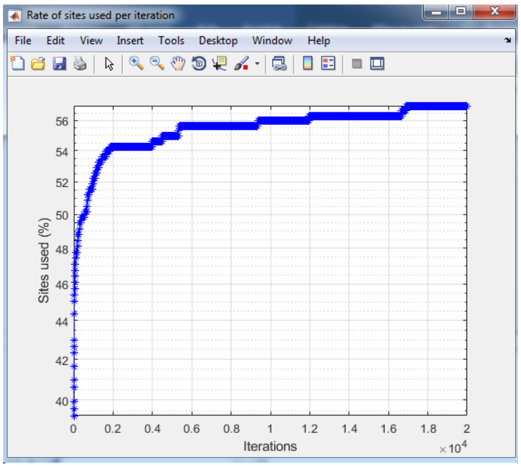

Fig. 9:- Evolution of the rate of sites used according to the number of iterations

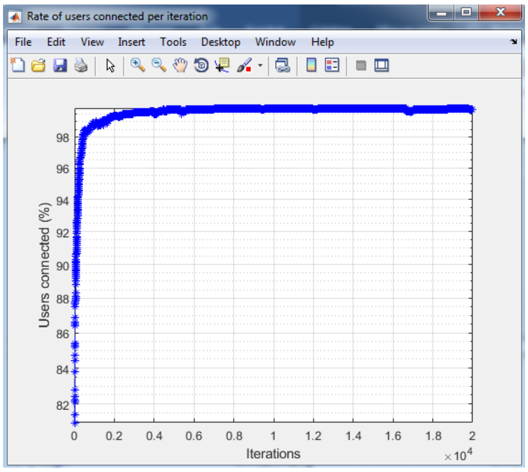

Fig. 10:- Evolution of the rate of users connected according to the number of iterations

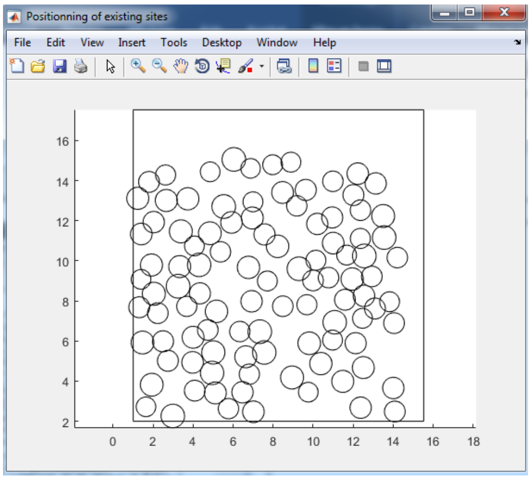

Fig. 11:- Positioning of fixed sites on the area of interest

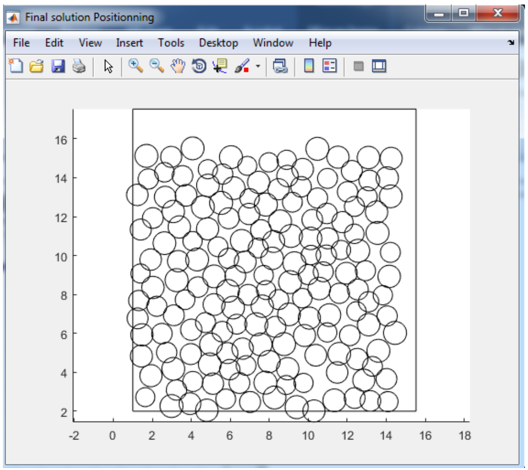

Fig. 12:- Final positioning of sites (fixed and added) on the area of interest

for $w_c = 0.4; w_t = 0.3; w_p = 0.2; w_e = 0.1;$ *number of particles*:100
Number of iterations :20000, **particle swarm optimisation**

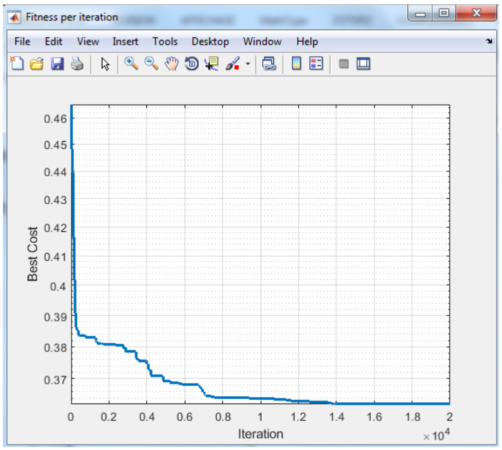

Fig. 13:- Evolution of the fitness according to the number of iterations

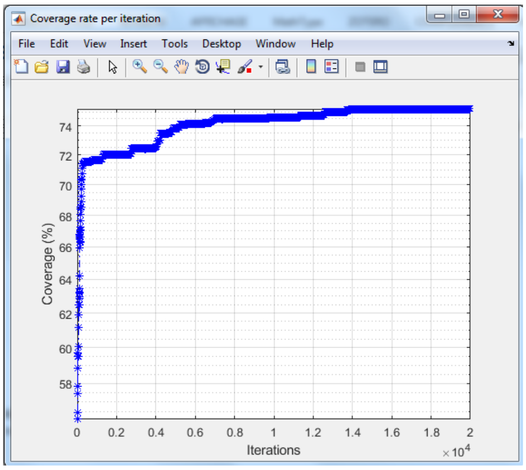

Fig. 14:- Evolution of the coverage rate according to the number of iterations

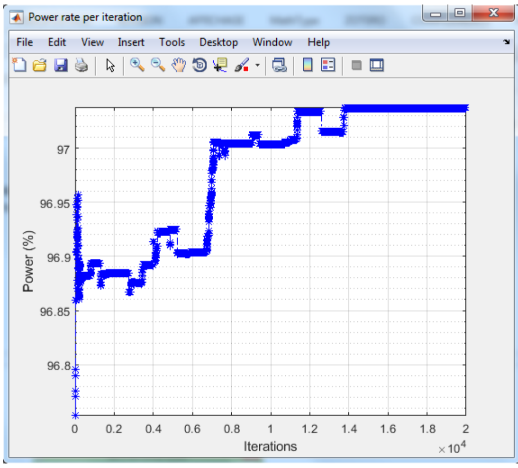

Fig. 15:- Evolution of the power used rate according to the number of iterations

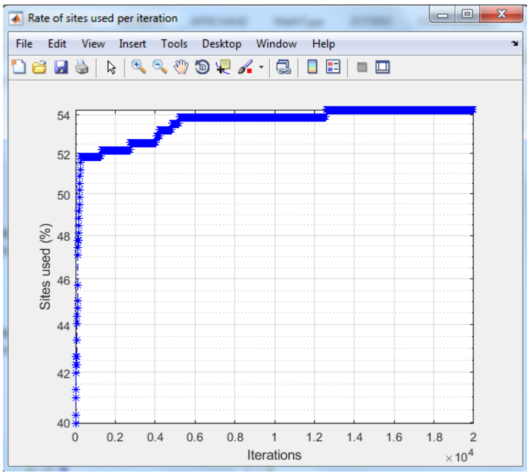

Fig. 16:- Evolution of the rate of sites used according to the number of iterations

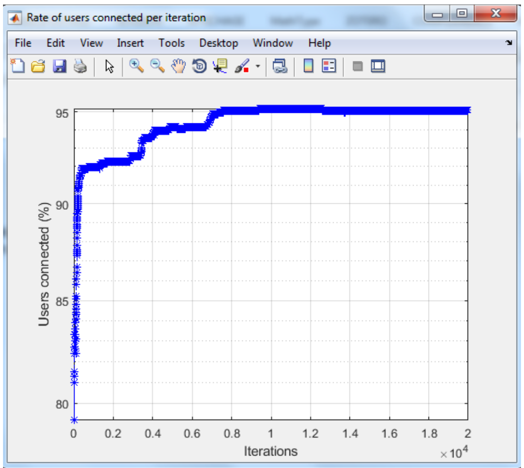

Fig. 17:- Evolution of the rate of users connected according to the number of iterations

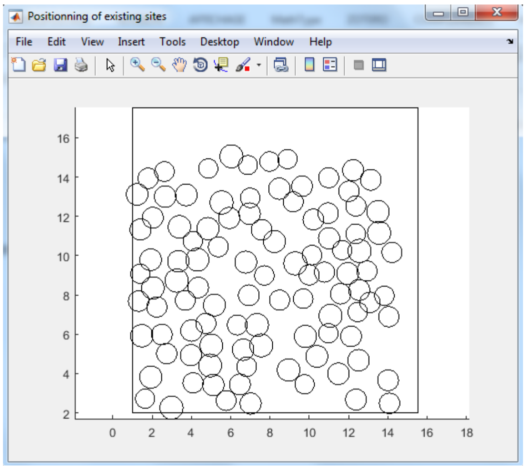

Fig. 18:- Positioning of fixed sites on the area of interest

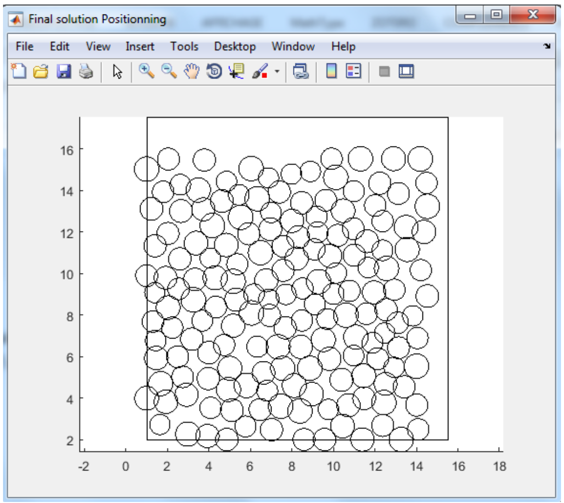

Fig. 19:- Final positioning of sites (fixed and added) on the area of interest

Joint results curves for GA and PSO, for an average of five (05) simulations of five (05) different instances each applied under the same basic conditions to GA and PSO on the following parameters:

Common weights, $w_c = 0.4$; $w_t = 0.3$; $w_p = 0.2$; $w_e = 0.1$; *Common number of iterations* :20000; *number of particles* :100 (*PSO*); *Number of individuals*:100; *selection by roulette*; *crossover* : *two point s*; *mutation*:*one point* (*AG*)

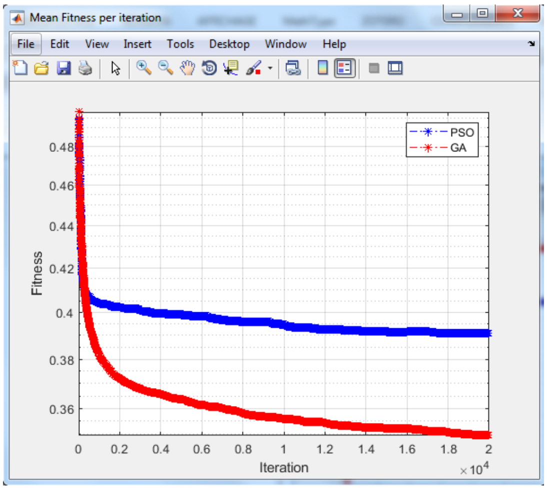

Fig. 20:- Comparison of the average Fitness according to the number of iterations (AG and PSO)

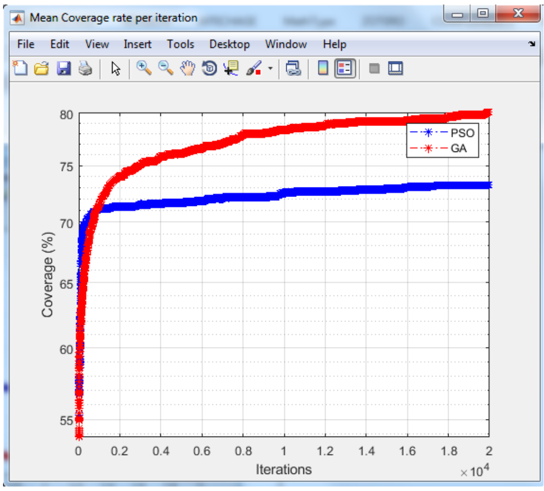

Fig. 21:- Comparison of the average of the Coverage according to the number of iterations (AG and PSO)

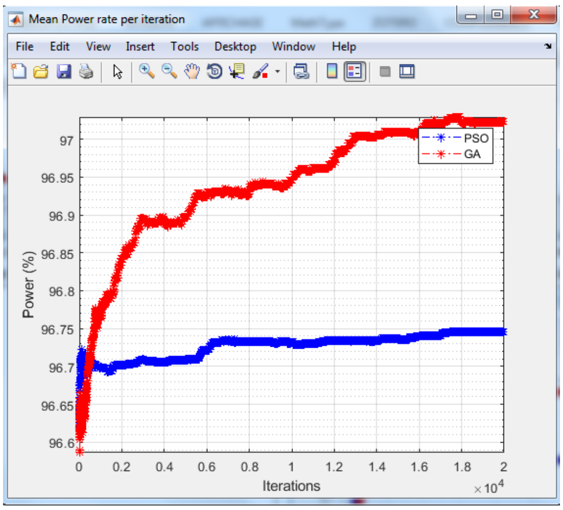

Fig. 22:- Comparison of the average energy consumption rates according to the number of iterations (AG and PSO)

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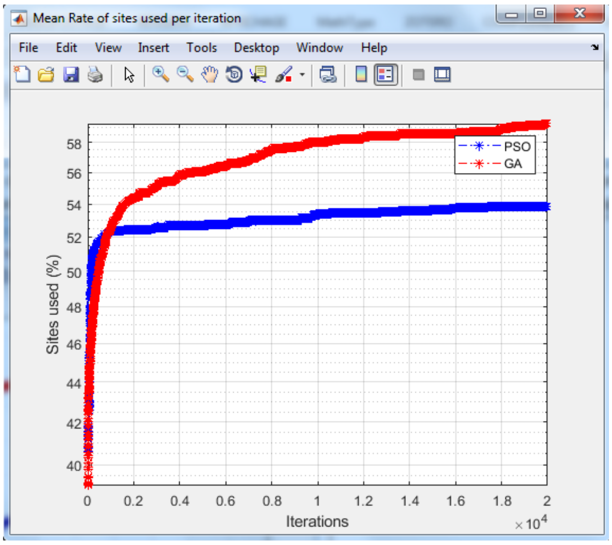

Fig. 23:- Comparison of the average rates of sites used according to the number of iterations (AG and PSO)

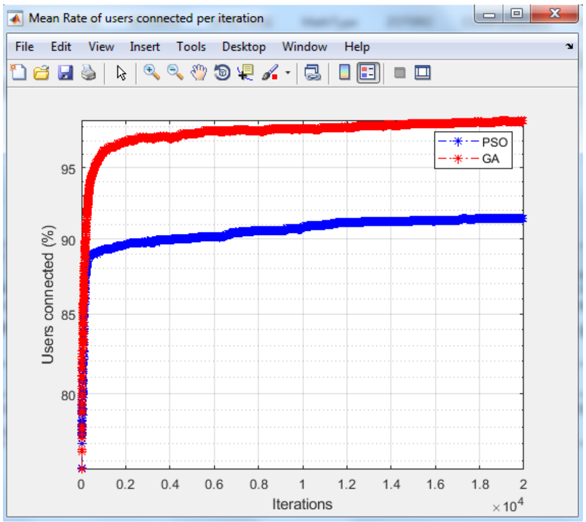

Fig. 24:- Comparison of the average of rates connected user by the number generations (AG and PSO)

Simulation results curves for comparison between PSO and AG selection by roulette - one-point crossover, selection by roulette - two-points crossover, selection by tournament - one-point crossover, selection by tournament , two-point crossover, selection-random, one point crossover, selection – random, two-points crossover.

Common weights, $w_c = 0.4$; $w_t = 0.3$; $w_p = 0.2$; $w_e = 0.1$; *Common number of iterations*: 20000; *number of particles*: 100 (*PSO*); *Number of individuals*: 100; *selection by roulette*; *crossover*: *two point s*; *mutation*: *one point* (*AG*)

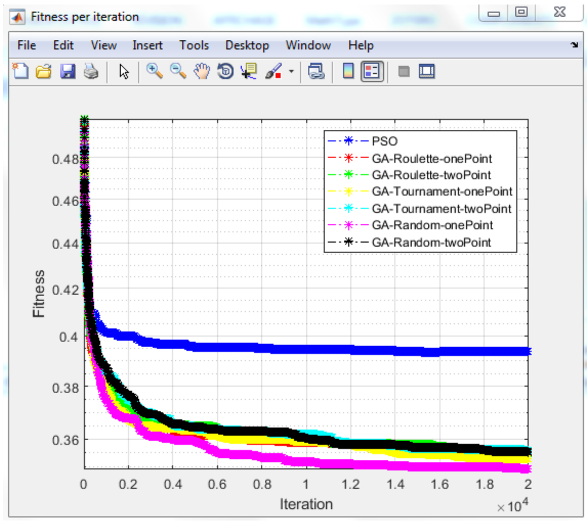

Fig. 25:- Comparison of various Fitness for AG and PSO according to the number of iterations

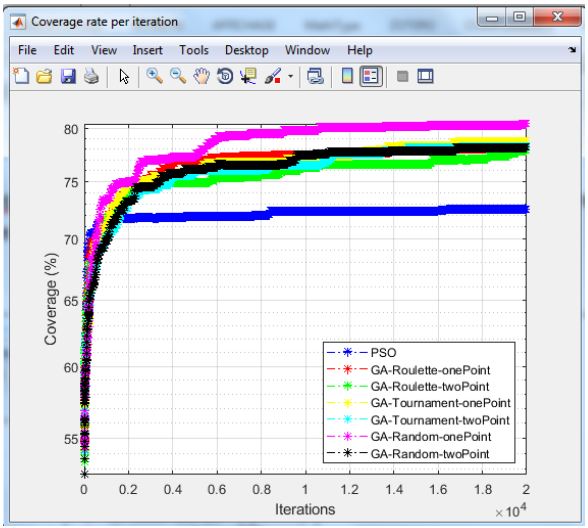

Fig. 26:- Comparison of the different coverage rates for AG and PSO according to the number of iterations

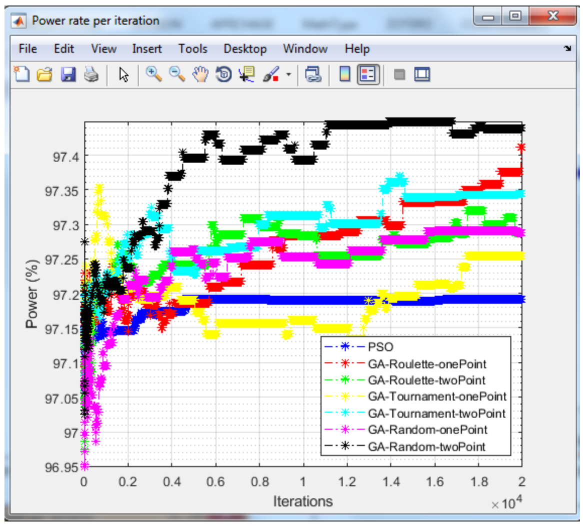

Fig. 27:- Comparison of different energy consumption rates for AG and PSO according to the number of iterations

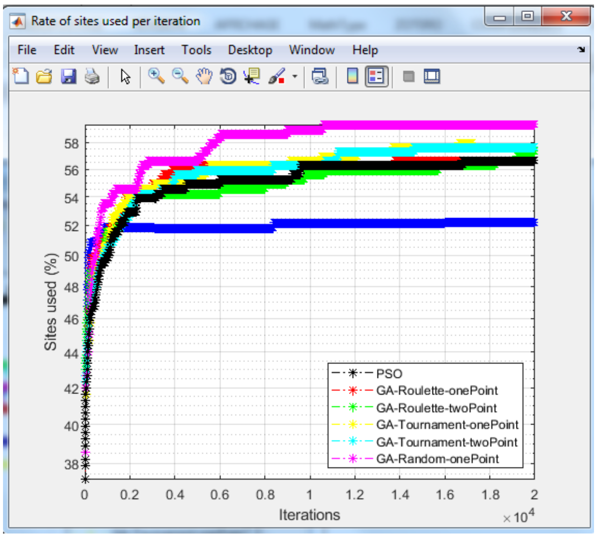

Fig. 28:- Comparison of different rates of sites used for AG and PSO according to the number of iterations

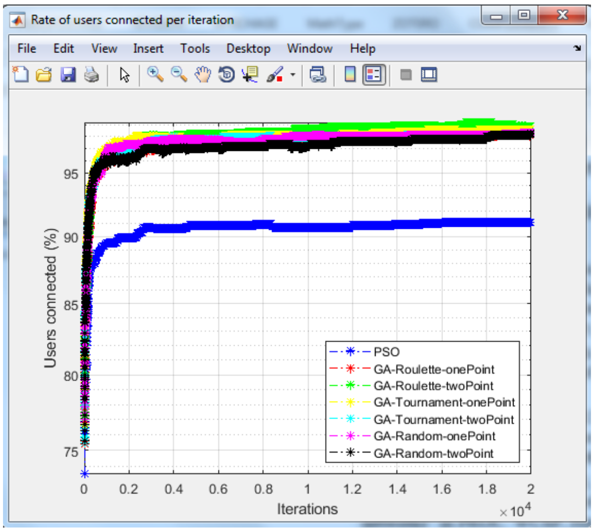

Fig. 29:- Comparison of different user connected rates for AG and PSO according to the number of generations

❖ *Comments*

In order to compare the performances of the genetic algorithm and particle swarm optimization for the problem of optimizing the migration from an existing network to a new network, their capabilities were examined through numerical results recorded in tables and graphical plots.

Looking at the above results, it appears that the genetic algorithm converges towards values of the objective function that are better than those produced by particle swarm optimization. This is also confirmed by the joint plots of the comparison curves between the GA and PSO which show a better evolution of the fitness by the genetic algorithms than that of particle swarms.

VI. CONCLUSION

In this article, we presented a comparison between the genetic algorithm and particle swarms to solve the problem of optimizing the migration of a given cellular network to a next-generation network.

A previously developed mathematical model has been re-proposed for the purpose of minimizing blackout areas, uncovered traffic, energy consumption and the number of base stations.

A genetic algorithm and a particle swarm optimization algorithm have been developed for the resolution of this problem.

From the results obtained, for the same instances, it appears that the two (02) algorithms address the problem of the optimal transition of networks as formulated.

However, the genetic algorithm provides, for this problem, better results than those of particle swarm optimization.

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