

A memetic algorithm approach for the planning and optimization of a new-generation cellular network capitalizing on existing sites.

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Abstract

In a context of technology migration, controlling the costs of deploying a new cellular network is essential. Several algorithmic approaches have proven themselves in the field of telecommunications for optimizing the placement of sites in an operator infrastructure. The work carried out in this article evaluates the effectiveness of a memetic approach in minimizing the cost of deploying the next generation cellular network. We model the cellular network migration problem as a question of optimization, which we resolve using this approach resulting from the combination of a genetic algorithm and a taboo search. Using the Jupyter tool, we created a model that takes as input an area in which a set of operational sites and potential locations of new sites are deployed. We then implement the genetic algorithm and then associate it with a taboo search based on the minimization of new sites and the reuse of existing sites. During testing, the proposed memetic approach uses 31 % of all sites; while the genetic algorithm alone uses 33%. In addition, we observe an increase in the coverage rate which goes from 76.1% to 86.4% with the memetic approach.

Keywords: *Optimization, network, Algorithm, Memetics, Genetics, Taboo search, deployment cost*

1. Introduction

Paced by increasing traffic demand and increasing throughput requirements, operators must constantly update their infrastructures to be able to meet customer demands and stay at the cutting edge of technology. However, updating operator networks requires costs. To minimize these costs, the reuse of existing sites is often used when deploying a new network. Indeed, using existing sites when implementing a new network makes it possible to reduce the cost deployment of this network. For example, we can implement a new 5G network on 2G, 3G sites see existing 4G. However, new generations of mobile networks, like 5G, use increasingly smaller cells due to the

support for higher speeds. In addition, 5G uses short-range waves, which considerably reduces traffic coverage. By optimally choosing the cells to complete, we minimize the cost deployment. Furthermore, a number of cells can be removed in a network without a major impact on its traffic coverage [1]. In order to reduce the cost of a network by ensuring excellent quality services, an appropriate network planning approach is necessary. Also, for a highly combinatorial and complex problem like this, an exhaustive search of all candidate solutions would be impossible [2]. Using an approach to find an acceptable solution

in a reasonable time would be the appropriate solution for this optimization problem.

This study is therefore interested in solving the problem of optimal deployment of a new network by considering an existing infrastructure. It is intended to show to some extent that using a hybrid approach would give better results than the Genetic Algorithm (GA) in [1]. His contribution results in the creation of a memetic algorithm resulting from a combination between a genetic algorithm and a taboo search (RT) applied to this optimization problem. The main objective is to minimize the cost of deploying a new cellular network with the satisfaction requirements: reduction of cutoff zones (satisfactory coverage), reduction of new sites to be deployed and reuse of existing sites.

This document is structured as follows: Section 2 is devoted to the literature review, section 3 is dedicated to the formulation of our optimization problem, sections 4 and 5 present the method and the resolution approaches used, in section 6, we proceed to the implementation of these approaches, sections 7 and 8 are successively allocated to the interpretation of the results obtained and to the discussion.

2. Literature Review

For a new mobile network to work like 5G, operators must deploy tens of thousands of antennas [3] throughout the area to be served. The choice of sites therefore turns out to be an essential step. Much research has focused on planning with the objectives of: optimizing coverage, capacity and reducing energy consumption. Among these works, we can cite, among others, the article on the optimization of 3G placement using genetic algorithms (GA) [4]. Faced with the high pace of implementation of 3G technology, the authors propose a GA to solve the problem of antenna placement to optimize coverage, increase the capacity of cellular networks of this generation in a period of time. The choice of this algorithm is justified by the advantage it has for multipoint search. The task of the algorithm is to find the best set of permitted

base station locations (60 in number) out of those possible to maximize coverage, improve quality of service and minimize network cost by reducing the number of base stations. The results obtained give satisfactory performance, that is, 98% of network users covered by a good quality signal. Furthermore, the work on the optimization placement and frequency assignment of antennas in a telecommunications network [5] offers us a method to optimize the location of antennas in conjunction with their frequency assignment. The objective here is to enable the development of a future decision support tool for the design of telecommunications networks. Also, it sets up a black box allowing simulations of a network and an optimization algorithm combining direct search and metaheuristics. He uses a simple network model based on the model of propagation of electromagnetic waves in a vacuum which he implements in the form of a computer program in C++ and then carries out simulations. In addition, with a view to improving the process of placing base stations, the work proposed in [6] sets up a solution for adapting two meta-heuristics based on local search, namely iterated local search. (ILS) and Breakout Local Search (BLS). This approach is based on local search with a disturbance of local optima in the search space as a diversification mechanism; It is thus characterized by a resetting of the search. The experimental results obtained as a result of the comparison between the proposed approach and other algorithms show that the approach improves the performance of these methods in most cases.

The works cited above focus on the placement problem by considering areas of interest devoid of existing operator infrastructure. In [1] on the other hand, an area already having sites is considered. Using the MATLAB tool, Raphael Nlend and Emmanuel Tonye propose a case of mobile network planning in a generation migration context, using GA. The objective being to minimize the cost of deploying the new network, ensure good traffic coverage while consuming less energy. With an area of 183 km², the coverage rate is estimated at 82.04% and the site utilization

rate is 41.97%. The results obtained show the efficiency of the use of approximate methods in this case, the genetic algorithm in the process of placing base stations.

However, the latter's work only applies to a specific area and the results are only true under these conditions. In addition, a study of approximate methods reveals that the use of a hybrid approach resulting from the combination of a genetic algorithm and local search could give us better results.

3. Problem Formulation

In our study, we address the problem of optimal positioning of new sites associated with sites already deployed for the establishment of a new cellular network. It is therefore a question within a set of potential sites $S = \{1, \dots, N_b\}$, finding the best network configuration which: maximizes network coverage by reducing new sites to be deployed.

We consider three main indicators: Minimization of the number of new sites $f_e(G)$ to be deployed, reuse of existing sites and maximization of the number of users covered by the network $f_c(G)$.

3.1 Optimization of the number of sites

The first essential point in reducing operator infrastructure costs is reducing the number of sites to be deployed. For this purpose, we will have to retain the network configuration using a minimum of possible sites as defined by the function

$$f_e(G) = \text{Min} \frac{\sum_{s=1}^{N_b} e_s}{N_b} \quad [1] \quad (1)$$

$$e_s = \begin{cases} 1 & \text{if the site is active} \\ 0 & \text{if the site is inactive} \end{cases} \quad [1] \quad (2)$$

The second point in reducing the cost of deploying a network is the reuse of existing sites in the area of interest. Or, reuse all existing sites.

3.2 Maximizing traffic and the number of users covered by the network

An operating network must meet the traffic demand of the maximum number of users in the

area of interest. The objective function which allows traffic to be maximized is given by:

$$f_c(G) = \text{Max} \frac{\sum_{s=1}^{N_b} A_s * e_s}{A_T} \quad [1] \quad (3)$$

With

A_s : The area covered by the site;

A_T : All the sites deployed;

And the function which minimizes the shadow areas is given by:

$$f_t(G) = \text{Min} \frac{U_T - \sum_{s=1}^{N_b} U_s * e_s}{U_T} \quad [1] \quad (4)$$

With :

U_s : The total number of users covered;

U_T : The total number of users

The coverage area of an antenna is all the points on the plan where the quality of the signal received from this antenna is sufficient to be able to carry out a communication. It is defined from the signal-to-noise ratio (SIR), as follows:

$$Z = \{(x, y) \in \mathbb{R}^2 : \text{SIR}_{dB}(x, y) \geq \text{SIR}_{dB}^*\} \quad [5] \quad (5)$$

With SIR_{dB}^* generally of the order of 10 dB [5]. For a user to be covered by a good quality signal, their distance (d) to the site must be less than or equal to the maximum distance for a good quality signal (d_{max}).

Let be :

$$d \leq d_{max} \quad (6)$$

Let

$$\begin{aligned} i &= (x_i, y_i) \\ j &= (x_j, y_j) \end{aligned}$$

The Euclidean distance $d(i, j)$ between i and j is given by:

$$d(i, j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \quad (7)$$

4. Method

We start from a general solution consisting of all existing locations and potential locations of new sites then, we improve this general solution by eliminating irrelevant locations, until a satisfactory solution is obtained using respectively the AG and the memetic algorithm.

4.1 Area to be served

The study area is represented by Cartesian coordinates. The abscissa and the ordinate vary respectively in the interval [0, 14.53] and [0, 15.53]. The surface area of the area to be served amounts to 14.53 km x 15.53 km. Inside this area, we define a fixed number of sites (100 sites) whose locations are already known. To this are added the different potential locations (500) which could accommodate new sites. Each base station is characterized by its location, antenna height, coverage radius, capacity.

We randomly deploy 1000 users following a uniform distribution. Each of these is characterized by its geographical location.

4.2 Propagation Model and Overlap Constraint

In this study, we place ourselves on a flat territory, without relief. Also, we work with the vacuum propagation model. Indeed, this model is the simplest for wave propagation. It is based on the following main hypotheses [2]:

- waves propagate in an empty medium. In practice, the fact that we are in the air and not in a vacuum has a negligible influence, and this hypothesis is therefore not too restrictive from this point of view. On the other hand, we do not consider the presence of obstacles;
- The transmitter is isotropic, that is to say it radiates the same power in all directions of space.

The free space propagation model is given by:

$$FSPL(f, m) = 20 \log_{10} \left(\frac{4\pi d f}{c} \right) \quad [7] \quad (9)$$

With :

d : distance between two antennas in free space (in m)

λ : Wavelength (in m)

Or even a weakening in free space with the ground

$$PL(d) = 40 \log(d) - 20 \log(h_T) - 20 \log(h_R) \quad [7] \quad (10)$$

With :

h_T : The height of the transmitting antenna

h_R : The height of the receiving antenna

5. Resolution Approaches

Meta-heuristics are these approximate methods making it possible to obtain a very good quality solution for problems arising from the fields of operational research or engineering. They are used to solve problems for which effective methods are not known to deal with them or, when solving the problem requires a lot of time or large storage memory.

In this article, we are particularly interested in approaches using GA and memetic algorithms.

5.1 A genetic algorithm

Genetic algorithms (GA) are stochastic optimization algorithms (use random variables) based on natural selection [8 – 9]. They emerged thanks to the work of David Goldberg and JOHN Holland in 1975 [10]. The vocabulary used is the same as that of genetics: individual (potential solution), population (set of solutions), genotype (representation of the solution), gene (part of the genotype), parent, child, reproduction, crossing, mutation, generation, etc. The operation of the genetic algorithm is simple, we start from an arbitrarily chosen initial population whose performance (Fitness) is evaluated on the basis of the set requirements. We create a new population of potential solutions using different principles (selection, spanning, crossover or recombination and mutation). Thus, only a few individuals are selected from the initial population and will be at the origin of the next generation and so on. The selected population will have the best characteristics and will therefore deduce the characteristics of the individuals of the following generation. The cycle starts again until a satisfactory solution is found. Genetic inheritance through generations allows the population to be adapted and therefore to better meet optimization criteria. Genetic algorithms have shown more efficiency in searching for global optimum than simulated annealing or tabu search [11].

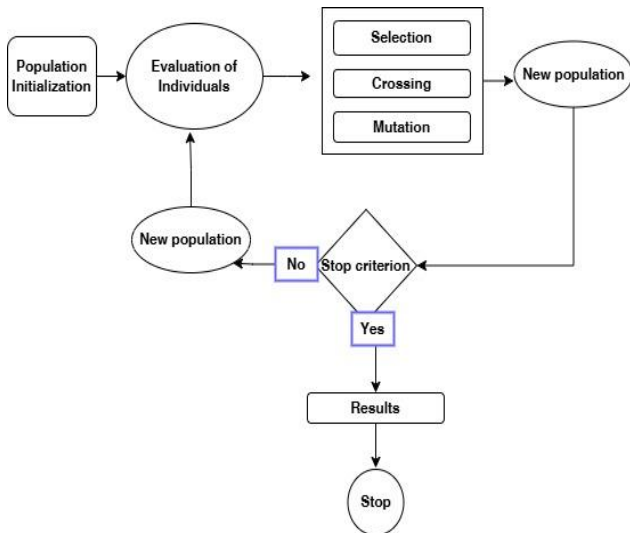


Figure 1. Genetic Algorithm Flowchart

5.2 A memetic algorithm

Memetic algorithms are hybrid genetic algorithms (combined with certain types of local searches) [12]. They were first proposed by Moscato [13-14]. The latter is quite simply based on the combination of population methods (ensures diversification) and local research methods (ensures intensification). The role of the GA is to explore the search space and detect potential regions with good solutions; the local search algorithm is used to make efficient use of the potential regions obtained by the GA. Indeed, the placement of a site can be done just as well with a local search approach as with a population approach.

However, although it is very precise, a local search approach only uses one solution at a time. Also, we will not be able to consider all the sites. Furthermore, a population approach gives us the possibility of working with all sites simultaneously. It supports several constraints and offers a diversification of solutions but does not allow in-depth exploration of the search space. A hybrid method combining these two approaches (search by solution population and local search) would beforehand give better results. In addition, it would be best suited to our placement problem which uses a large number of components (variables) simultaneously. The use of the GA would allow us to detect potential regions with good solutions and a taboo search algorithm would subsequently allow us to efficiently explore the potential regions defined by the GA.

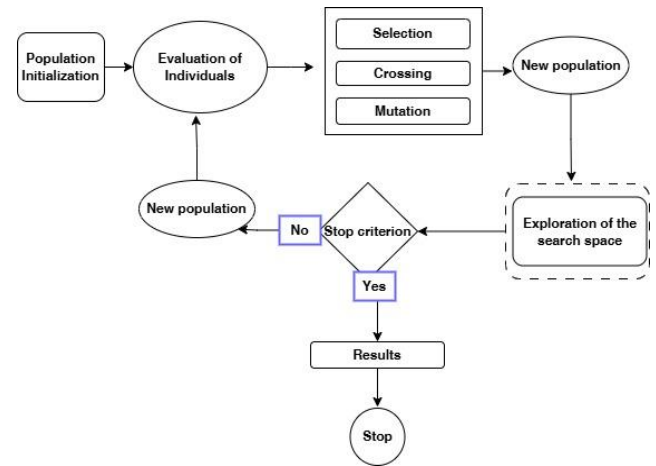


Figure 2. Flowchart of the proposed memetic algorithm approach

6. Implementation

Our implementation is carried out using the opensource Anaconda 3 distribution for python programming. We work with the Jupyter code editor.

6.1 Area to be served and users

We randomly deploy our 1000 users (U_T) from the network. We use here the same number of users as defined in [1].

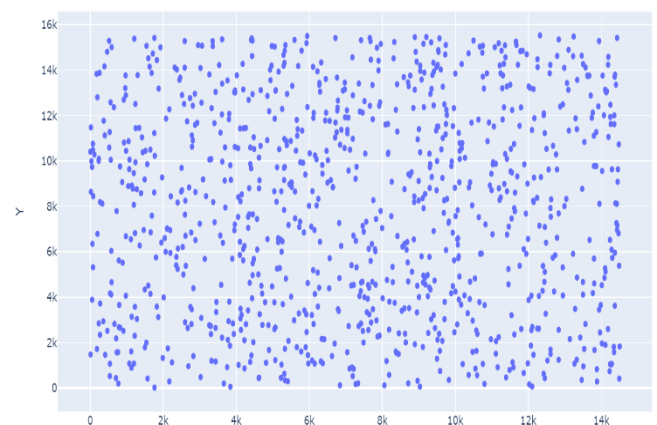


Figure 3. Distribution of different network users

6.2 Sites initially deployed

In our study area, we deploy 100 operational sites (sold)[1], they are characterized by isotropic antennas and represent the network configuration before the migration process.

Fig.4 represents the distribution of sites following a normal law.



Figure 4. Distribution of initial sites

Following Fig.4, we will add well-chosen sites to increase coverage and satisfy traffic demand.

6.3 Potential locations of new sites

In our territory, we define a set of points representing the areas where it is possible to deploy a new site (because in a real environment, it is not possible to do it anywhere).

Fig.5 represents the potential locations that could potentially accommodate new sites.

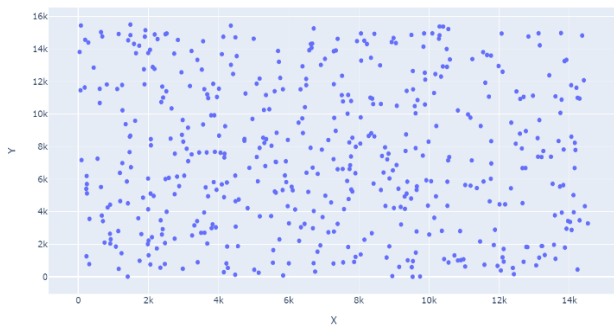


Figure 5. Distribution of potential locations that could accommodate new sites

It is in this set of positions that we will select where to deploy our new sites considering the pre-existing sites defined in fig.4.

6.4 Genetic Algorithm Implementation

We start with a complete initial solution consisting of all sites (existing sites and potential locations of new sites) that we improve.

Data coding: we are interested in one of the main parameters which is coverage. Also, the radius of each site will determine the number of users covered and influence the number of sites to deploy. Each site will be characterized by its coordinates, radius and height;

Generation of the initial population: our initial population is characterized by sites already existing on the ground (to be reused). To this, we

add a set of potential positions that additional sites could occupy. **Adaptation function (Fitness):** the performance of each site is evaluated based on the number of users covered. Also, the fewer users the site has covered, the less useful it is;

Selection: The selection process is done by elitism, only the sites best meeting the requirements will be selected. The main criterion remains the capacity (number of users supported) of each site. To ensure excellent coverage, we set the selection probability to be 0.03 for a new site to be selected. Indeed, considering the distribution and number of populations, a greater probability increases the uncovered areas. We then focus on interference. Sites that are too close to each other will undergo a second evaluation and only the best will be selected. Given that one of the objectives is to reuse sites already on the ground, these will remain priority over new locations;

Crossing: It will be done at a point, particularly at the level of the radius between the closest locations;

Mutation: Depending on the sites present in the field, numerous predefined sites will be selected randomly and will undergo a potential mutation. In particular a variation of the coverage radius depending on the maximum traffic coverage which is 20 users.

The stopping criterion: For interrupting the algorithm, we set a maximum number of iterations (500 iterations) before stopping the algorithm.

6.5 Taboo research integration

The search process with the genetic algorithm completed, we will subsequently proceed to a second evaluation of our search space to refine the results obtained as illustrated in fig.2. For each site selected, the algorithm will again evaluate neighbouring locations and select the one that best meets the set requirements. The stopping criterion for interrupting the algorithm is the maximum number of iterations without solutions improving the result previously retained in the Taboo list. Final location selection will consider a minimum distance between sites to minimize interference.

Table 1. Parameters used

Setting		Value	Reference
U_T		1000	[1]
S_{old}		100	[1]
Potential locations		500	
Probability of selection		0.03	

7. Results and Interpretations

7.1 Genetic algorithm

The curve generated in fig. 6 illustrates the evolution of the selection of locations for new sites over the iterations

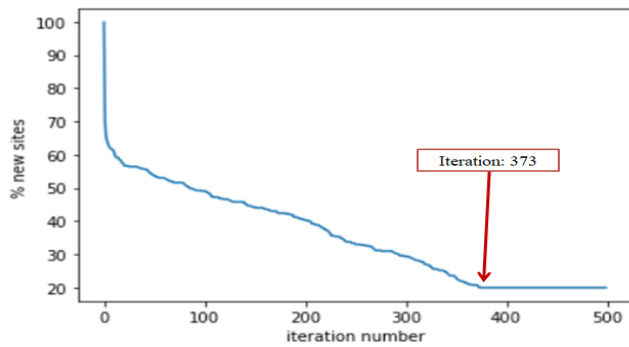


Figure 6. Evolution of site use depending on the number of iterations

We notice that the curve gradually decreases. This is due to a decrease in the number of potential locations in the network. Thus, during implementation, locations that do not meet the selection criteria will be eliminated. In addition, the number of deployed sites will stabilize from iteration 373. We observe that the number of sites deployed on all predefined potential locations is 20%.

Fig.7 presents the behaviour of the network coverage rate during the iterations.

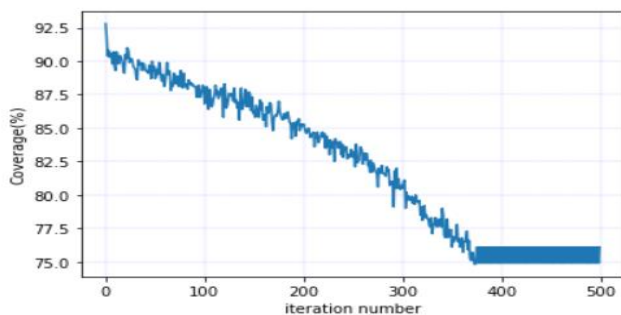


Figure 7. Variation in the number of users covered depending on the number of iterations

The different variations of the curve are justified by a modification of the network coverage at each iteration. Indeed, the processes of crossings and mutations continually vary the coverage radii of the different sites, which has a great influence on the number of users covered.

With 20% of the new locations deployed (fig.6), we obtain a maximum coverage of 76.1% (fig.7).

Fig.8 is a representation of the use of sites in the field (old and new).

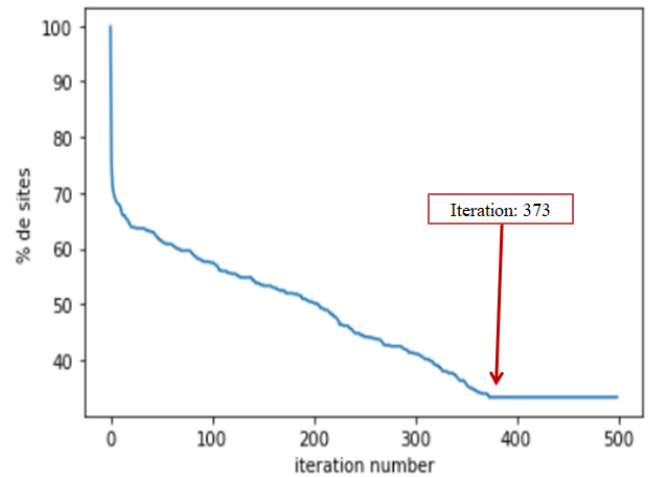


Figure 8. Evolution of the total number of sites depending on the iterations

The curve will decrease until iteration 373. Then, it stabilizes from iteration 373 because it will have reached its minimum which is 33%. This percentage represents the rate of sites in the field after removing irrelevant locations. All that remains are all existing sites and locations selected from the predefined potential locations.

7.2 Integration of Taboo research

By combining Taboo research with the genetic algorithm, we observe an increase in the number of iterations before obtaining a network configuration using the minimum number of sites. The number of iterations before obtaining an acceptable solution increase. However, the number of selected sites decreases more quickly with slight variations during the iterations.

Fig.9 illustrates the evolution of the use of the new sites throughout the iterations after integration of Taboo search into the GA.

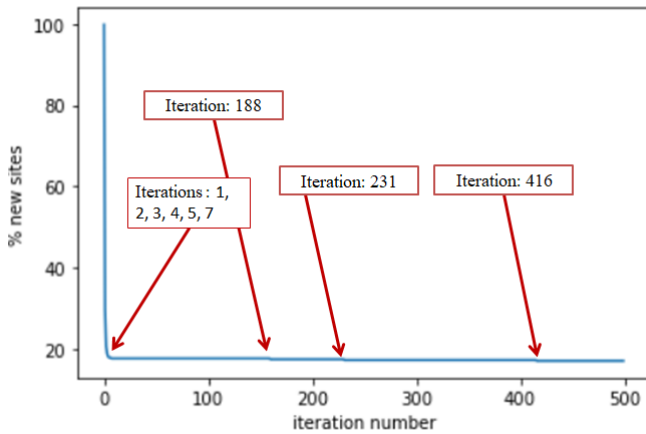


Figure 9. Evolution of site use based on iterations (proposed memetic algorithm)

The curve undergoes fewer variations (iterations 1, 2, 3, 4, 5, 7, 188, 231, 416) than with the AG, then definitively stabilizes from iteration 416. Indeed, after the iteration 416, there are only sites that best meet the requirements set. We observe in fig.9 a minimum rate of sites added of 17.2% which is lower than that obtained in fig.6.

Fig. 10 is a representation of the variation in network coverage as a function of the number of iterations after integration of the Taboo search

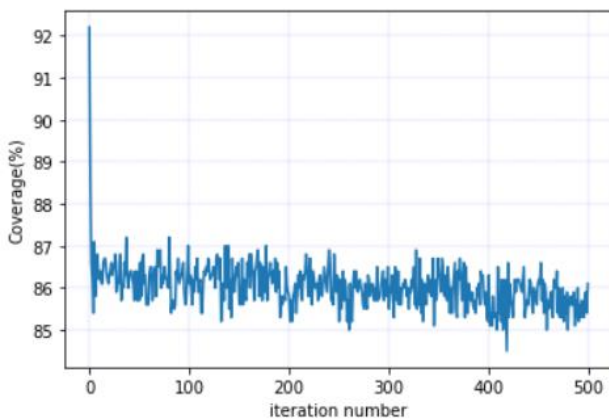


Figure 10. Coverage variation depending on the number of iterations (memetic algorithm)

Focusing on network configurations that uses the minimum possible sites (between iteration 416 and iteration 499), the maximum coverage is 86.4% (at iteration 468). So, with 17.2% new sites, we have 86.4% coverage, a value higher than that obtained in fig.7.

Fig.11 is a representation of the use of sites in the field (old and selected locations).

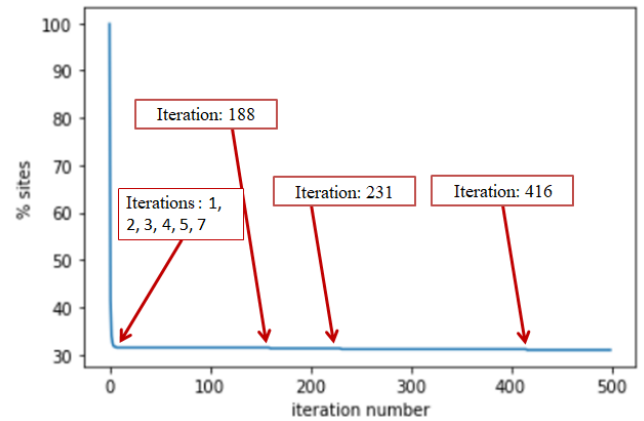


Figure 11. Evolution of the total number of sites according to iterations (memetic algorithm)

We observe in fig.10 slight variations at iterations 1, 2, 3, 4, 5, 7, 188 and 231. The last perceptible variation is at iteration 416. Beyond this, the curve stabilizes definitively because it will have reached its minimum which is 31%. The minimum rate of sites deployed with the memetic approach is therefore lower than that obtained with the AG as illustrated in fig.8.

Fig 12 is the illustration of the distribution of sites with the proposed memetic algorithm.



Figure 12. Best network configuration obtained over 500 iterations with the memetic algorithm

It shows us the distribution of sites after adding new sites to our network.

Table 2 gives a summary of the rates of the sites used in depending on the different approaches.

Table 2. Network configuration using minimum sites

Method	Rate of new sites used	Iteration
Genetic algorithm	20%	373
Memetic algorithm	17.2%	416

We actually note a reduction in the number of sites with the use of the memetic approach i.e., 2.8% less than with an AG approach. However, the GA converges more quickly to the minimum sites (iteration 373) than the memetic algorithm (iteration 416).

Table 3 gives us a summary of the maximum coverages obtained with the use of the different approaches.

Table 3. Coverages obtained with the different approaches for a network configuration using the minimum number of sites

Method	Coverage	Iteration minimum
Genetic algorithm	76.1%	375
Memetic algorithm	86.4%	468

The memetic approach is once again better because it offers us greater coverage (86.4%) than that obtained with the GA (76.1%).

Table 4 shows us the rates of sites deployed with the two approaches.

Table 4. Rates of sites selected from predefined potential locations

Method	Rate of sites used
Genetic algorithm	33%
Memetic algorithm	31%

The GA uses more sites than the proposed memetic approach (tab.4) with a lower coverage rate as shown in tab.3.

8. Discussion

This article proposes a hybrid (memetic) approach to site placement for the optimal deployment of a new cellular network. It is part of a technology migration process with reuse of existing sites. The results obtained depend on users, existing sites, and potential locations of new sites. The tests carried out with the different approaches (table 2, table 3, table 4), show us that a hybrid approach resulting from a combination of genetic algorithms and taboo research applied to the placement of sites, gives us better results than the use of genetic algorithm approach only. Indeed, the proposed memetic approach considerably

improves the results obtained with the GA, we note a reduction in the number of sites (20% with the GA to 17.2% with the memetic approach) for an increase in coverage (76.1% with GA to 86.4% with the memetic approach). In addition, by leaving it to our approach to give us the different possible configurations of the network (depending on the coverage of users and the number of sites), it submits to our appreciation a multitude of possible configurations and allows, if necessary, to choose the one that suits us best. The results obtained depend on the parameters set; A modification of any of these will lead to different results, hence this study aims to some extent at the development of a tool to support the planning of next generation networks. Furthermore, the application of a memetic approach to [1] would considerably improve the results obtained as demonstrated throughout our study.

9. Conclusion

In this article, we implemented a memetic algorithm to the problem of optimal deployment of a new network in mobile telephony. The study is part of a process of migrating technologies from an old generation to a new generation of mobile network. The proposed algorithm allows better control of the cost of operator infrastructures by significantly reducing the sites to be deployed (reduction linked to maintenance, rental or purchase of land and even energy consumption). The results obtained clearly demonstrate the effectiveness of using a memetic approach in the placement process. Unlike using the genetic algorithm only approach as proposed in [1]. Our approach is more efficient because, in addition to providing better coverage, it gives us network configurations using fewer sites than the genetic algorithm approach, which fits well with the objectives set.

Nomenclature

A_T	Totality of deployed sites
A_s	Area covered by the site s, km m ²
c	Celerity of light, ms ⁻¹
d	

d_{max}	Distance, m
e_s	Maximum distance, m
	State of the site
f	Frequency, Hz
h_R	Receiver height, m
h_T	Transmitting antenna height
U_T	Total number of users
U_S	Total number of users covered
SIR	Signal-to-noise ratio, dB

References

1. Raphael Nlend, Emmanuel Tonye (2019). Planning and Optimization Approach Using Genetic Algorithm of a New Generation Cellular Network Capitalizing on the Existing Sites. International Journal of Science and Research. <http://dx.doi.org/10.21275/17051902>
2. I.K. Valavanis, G.E. Athanasiadou, D. Zarbouti, G.V. Tsoulos. (2014). Base-Station Location Optimization for LTE Systems with Genetic Algorithms, IEEE.
3. Tasona D.J. Tanguy, Matanga Jacques, Malong Yannick. (2022). The Antennas of Next Generations. Review of Computer Engineering Studies Vol.9, No.4. pp.141-144 <https://doi.org/10.18280/rces.090403>
4. Job Munyaneza, Anish Kurien, Ben Van Wyk. (2008) Optimisation of Antenna Placement in 3G Networks Using Genetic Algorithms. Third International Conference on Broadband Communications, information Technologie and Biomedical Application. <https://doi.org/10.1109/BROADCOM.2008.20>
5. Alexandre Marty. (2011). optimization of the placement and frequency assignment of antennas in a telecommunications network. Department of mathematics and industrial engineering Ecole Polytechnique de Montréal.
6. Larbi Benmezal, Belaid Benhamou, Dalila Boughaci. Some Neighborhood Approaches for the Antenna Positioning Problem. ICTAI 2017: 1001-1007. <https://doi.ieeecomputersociety.org/10.1109/ICTAI.2017.00154>
7. Randrianjanahary Arthur (2018). 5G network sizing. Polytechnic Higher School University of Antananarivo.
8. D.E Goldberg, (1989). Genetic Algorithms in search, Optimization and Machine Learning. In Wokingham, Addison-Wesley.
9. J. H. Holland (1975). "Adaptation in Natural and Artificial Systems," University of Michigan Press, Ann Arbor, MI.
10. Sidi Mohamed Douiri, Souad Elbernoussi, Halima Lakhbab. Exact Resolution Heuristics and Metaheuristics. Mohammed V University. Faculty of Sciences of Rabat, Mathematics, Computer Science and Applications Research Laboratory.
11. Lakshminarasimman N, Baskar S, Alphones A, Willjuice Iruthayarajan M (2013). Base Station Placement for Dynamic Traffic Load Using Evolutionary Algorithms, Wireless Pers Commun <https://doi.org/10.1007/s11277-013-1036-9>.
12. Dalila Boughaci. (2021). Solving optimization problems in the fifth generation of cellular networks by using meta-heuristics approaches. 17th International Learning and Technology Conference 2020 (17th L and T Conference). Procedia Computer Science 182.p 56-62. <https://doi.org/10.1016/j.procs.2021.02.008>
13. P. Moscato. (1989). On Evolution Search Optimization Genetic Algorithms and Martial Arts: Towards Memetic Algorithms', Caltech Concurrent Computation Program, C3P Report, 826.
14. P. Moscato, and M.G. (1992). A memetic approach for the traveling salesman problem implementation of a computational ecology for combinatorial optimization on message-passing systems', In Valero et al. (Eds). Parallel Computing and Transputer Applications, pp.177-186.
15. Imad Alawe, Adlen Ksentini, Yassine Hadjadj Aoul, Philippe Bertin. (2018) Improving Traffic Forecasting for 5G Core Network Scalability: A Machine Learning Approach. IEEE Network 32(6): 42-49. <https://doi.org/10.1109/MNET.2018.1800104>
16. RAPPAPORT, T. S. (2002). Wireless Communications: principles and practice. Prentice Hall, seconde edition.

17. H.H Hoos and T. Sttzle. (2004). Stochastic Local Search Foundations and Applications'. in Morgan Kaufmann / Elsevier.
18. F. Glover. (1994). Tabu search for nonlinear and parametric optimization. Discrete Appl. Math. (49) 231- 255. [https://doi.org/10.1016/0166-218X\(94\)90211-9](https://doi.org/10.1016/0166-218X(94)90211-9)
19. Robert Falkenberg, Benjamin Sliwa, Nico Piatkowski, Christian Wietfeld, (2018), Machine Learning Based Uplink Transmission Power Prediction for LTE and Upcoming 5G Networks using Passive Downlink Indicators. <https://doi.org/10.1109/VTCFall.2018.8690629>
20. Metin Öztürk, Mandar Gogate, Oluwakayode Onireti, Ahsan Adeel, Amir Hussain, Muhammad Ali Imran. (2019). A novel deep learning driven, low-cost mobility prediction approach for 5G cellular networks: The case of the Control/Data Separation Architecture (CDSA). Neurocomputing 358: 479-489. <https://doi.org/10.1016/j.neucom.2019.01.031>
21. Ruchi Sachan, Tae Jong Choi, and Chang Wook Ahn. (2016). A Genetic Algorithm with Location Intelligence Method for Energy Optimization in 5G Wireless Networks. Hindawi Publishing Corporation Discrete Dynamics in Nature and Society. <http://dx.doi.org/10.1155/2016/5348203>
22. Indar Surahmat. (2021). Evaluation of Antenna Placement in Urban-Road Scenarios on Beam Alignment of 5G Millimeter-Wave Small Cells, Published by Atlantis Press. <http://dx.doi.org/10.2991/aer.k.210204.036>
23. Ali Ghorbanian, Mehdi Neyestani. (2018). A New Approach to Community Detection in Complex Networks by Using Memetic Algorithms. https://doi.org/10.18280/ama_a.540301