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X_2 BI-CRITERIA OPTIMIZATION OF eNodeB IN AN eUTRAN NETWORK USING LTE TECHNOLOGY

BROU Pacôme*, PANDRY Ghislain and DIOMANDE Siaho

Laboratoire des Sciences Technologiques de l'Information
et de la Communication (LASTIC)
Equipe Mathématique Algorithme Complexité (MAC)
Ecole Supérieure Africaine des Technologies de l'Information
et de la Communication (ESATIC)
Cote d'Ivoire

Laboratoire des Sciences Technologiques de l'Information
et de la Communication (LASTIC)
Equipe Optique Non-linéaire, Réseaux Optiques
et Télécommunication (ONET)
Ecole Supérieure Africaine des Technologies de l'Information
et de la Communication (ESATIC)
Cote d'Ivoire

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*Corresponding author

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Laboratoire des Sciences Technologiques de l'Information
et de la Communication (LASTIC)
Equipe Intelligence et Sécurité des Systèmes Numérique (I2SN)
Ecole Supérieure Africaine des Technologies de l'Information
et de la Communication (ESATIC)
Cote d'Ivoire

Abstract

The optimal deployment of eNodeB in an eUTRAN LTE network is a key challenge to ensure efficient coverage and minimize inter-cell interference, while meeting quality of service (QoS) requirements. This paper proposes a dual criteria dimensioning approach based on a genetic algorithm, aimed at simultaneously optimizing network coverage and interference management, two aspects essential for the performance of LTE networks in dense urban environments. The developed model is based on a multi-objective mathematical formulation, integrating two optimization functions: maximization of coverage by optimizing the spatial distribution and transmitting power of eNodeB, and minimization of inter-cell interference by adjusting the frequency configuration and spacing of base stations. The genetic algorithm used enables efficient exploration of the solution space by applying evolutionary operators (selection, crossover and mutation) to seek an optimal balance between these two objectives. Simulations carried out on scenarios show that the proposed genetic approach delivers an 18% improvement in coverage and a 22% reduction in interference compared with the fixed hexagonal planning method. The results obtained demonstrate that the bi-criteria genetic approach enables optimized management of the LTE network, improving QoS while guaranteeing efficient use of spectrum resources, but remains highly dependent on the genetic operators' parameterization. Conversely, due to the Pareto front, dynamic optimization of the LTE network is achieved, maximizing coverage by 90% while minimizing interference by 22.7% in high-density urban environments. This study thus provides a robust and scalable solution for the strategic deployment of eNodeB in next-generation networks.

1. Introduction

The meteoric rise of mobile technologies and the explosion in data traffic are forcing telecoms operators to rethink the dimensioning and optimization of their LTE networks. In an eUTRAN network, eNodeB are central elements, ensuring not only coverage and connectivity for users, but also interference management and quality of service (QoS). Optimal sizing of these base stations is therefore of strategic importance to meet performance and energy efficiency requirements in increasingly dense environments. Among optimization approaches, genetic algorithms stand out for their ability to efficiently explore large spaces of non-linear solutions, offering a robust method for dealing with multi-criteria optimization problems. However, in many cases, the simultaneous consideration of two essential criteria - for example, maximizing coverage and minimizing interference - results in a particularly complex dual-criteria optimization challenge. This problem calls for the development of precise mathematical models and suitable solving methods to identify optimal trade-offs that guarantee satisfactory QoS while keeping costs and deployed resources under control. This research paper proposes a bi-criteria mathematical model based on genetic algorithms for sizing eNodeB in an eUTRAN network using LTE technology. The objective is to simultaneously define and optimize two key criteria: network coverage and inter-cell interference reduction. We detail the problem formulation, including operational and QoS constraints, as well as the algorithmic method used to explore the solution space. Finally, comparative simulations demonstrate the effectiveness of the proposed approach compared with conventional optimization methods, paving the way for more efficient and resilient LTE networks in the face of the challenges of an ever-changing urban environment.

2. State of the Art

Over the last five years, LTE (long-term evolution) network optimization has grown rapidly, particularly with the use of heuristic techniques to configure eNodeB base stations in the eUTRAN (evolved universal terrestrial radio access network). In most of the work reviewed, cell dimensioning was resolutely centered on single-criteria optimization, i.e., on a single criterion such as coverage, capacity or interference reduction, and proved remarkably effective in improving network performance while minimizing costs. Thus Hua et al. investigated the optimization of power consumption of eNodeB base stations in eUTRAN using genetic algorithms. By minimizing transmission power and dynamically adapting coverage parameters, they observed a substantial reduction in energy consumption with no negative impact on QoS [1]. In 2019, Liu et al. focused their work on optimizing eNodeB coverage in dense urban environments. They demonstrate that the genetic algorithm can improve network coverage while reducing interference through optimal transmit power configuration [2]. In 2020, Alshahrani et al. defined a single-criteria optimization model focused on network capacity, while showing how genetic algorithms can maximize eNodeB capacity by adjusting antenna and power parameters [3]. Rahman et al. in 2020 explored the reduction of cell-to-cell interference through genetic optimization that dynamically adjusts the transmission power of eNodeB. The results show that interference reduction improves QoS stability for users in urban areas [4]. In the same vein, Kim and Lee, in the first post-COVID year (2021) applied a single-criteria optimization approach to minimize interference using a genetic heuristic that adapts transmitter parameters in real time to maximize network performance without compromising end-user coverage [5]. In the same year 2021, Chen et al. focused instead on a comparative work of several genetic optimization strategies for eNodeB in urban environments, focusing on interference reduction, the findings demonstrating improved coverage and capacity through genetic algorithms thus enabling adaptive configuration [6]. In another study, Alam and Yu in 2021 developed a single-criteria optimization model to maximize the energy efficiency of eNodeB; at the end of their study, the authors show that energy efficiency can be significantly improved by adjusting transmission parameters in both directions using the genetic algorithm [7]. In the year 2022, the work of Ahmed and Chen showed that optimizing network capacity under the constraint of adjusting antenna and frequency parameters on the one hand,

and adjusting bandwidth and transmission power configurations on the other, optimizes eUTRAN network capacity by reducing latency in urban environments [8], however, Bakhshi and Zarei showed that optimization based on a single criterion in dense, highly connected LTE networks in urban environments does not meet QoS requirements as specified in the specifications, which is why these authors suggest integrating several criteria for a more comprehensive optimization [9]. In 2023, Wang and Lin [10] and Deng and Song [11] proposed an optimization model for eNodeB coverage in suburban, peri-urban and rural areas. Tests carried out on the optimization model with the genetic algorithm enabled significant coverage improvements to be observed by modifying antenna orientations and adjusting power levels, while reducing base station energy consumption; still in the same vein, Singh and Gupta in 2023 developed a predictive traffic model with genetic algorithms that adjusts traffic according to traffic periods, while ensuring a reduction in energy consumption during periods of low traffic [12]. Finally, in 2024, Jiang and Wu put forward an optimization model for interference management in LTE networks by applying a genetic optimization approach centered on a single criterion, demonstrating that this approach reduces interference while maintaining appropriate coverage levels [13]. Zhou and Liang focused their research on the energy consumption of eNodeB without affecting coverage in LTE networks. The results of this research show promising potential for low-energy networks [14].

This research demonstrates the diverse applications and benefits of genetic algorithms for single-criteria optimization of eNodeB in LTE networks, whether to improve coverage, reduce interference, maximize capacity or reduce energy consumption. They also highlight the relevance of this approach for optimizing performance in increasingly complex and diverse environments. Sizing eNodeB in an eUTRAN LTE network is a complex problem requiring optimization of several parameters to guarantee optimal network coverage while minimizing inter-cell interference. In this context, this paper proposes a bi-criteria mathematical model, optimized using a genetic algorithm, aimed at balancing these two conflicting objectives: maximizing network coverage while minimizing inter-cell interference, taking into account several technical and economic constraints such as network capacity, budgetary cost of infrastructure deployment, latency thresholds, etc.

3. Optimization Model for the Bi-criteria Problem of eNodeB in LTE Technology Using the X_2 Interface

3.1. Decision variables

- n : Number of eNodeB to be deployed, with $N = \{1, \ldots, n\}$.

- P_i : eNodeB transmit power i (in dBm).

- x_i : eNodeB position i (localization (x_i, y_i)).

- f_i : eNodeB's frequency i.

- $\delta(f_i, f_j)$: Same frequency indicator: $\delta\begin{cases} 1 & \text{if } f_i = f_j \\ 0 & \text{otherwise.} \end{cases}$

- d_i : Distance between eNodeB i and eNodeB j.

- C_i : eNodeB i coverage, expressed as a percentage of territory covered.

3.1.1. Parameters

- $I_{\max}$: Maximum tolerated interference threshold.

- $C_{\max}$: Minimum coverage required (%).

- α : Signal attenuation factor.

- β : Interference attenuation factor.

- ζ : Total available bandwidth.

- ω_1 : Relative importance of coverage.

- ω_2 : Relative importance of interference minimization.

3.2. Bi-criteria optimization model

3.2.1. Definition of the bi-criteria fitness function

The fitness function is composed of two modeled objective functions that must be optimized simultaneously.

- Function: f_1 of maximizing network coverage.

Subjective: Ensure that the total coverage provided by all eNodeB covers as much of the territory as possible, while avoiding uncovered areas

$$\text{Max } f_1 = \sum_{i=1}^{n} C_i,$$

where $C_i = \frac{P_i}{d_i^{\alpha}}$.

- Inter-cell interference minimization function f_2, whose aim is to optimize the interference caused by the simultaneous use of the same frequencies between adjacent cells:

$$\text{Min } f_2 = \sum_{i=1}^{n} \sum_{j>i}^{n} I_{ij},$$

where $I_{ij} = \frac{P_i \cdot P_j}{d_{ij}^{\beta}} \cdot \delta(f_i, f_j)$.

3.2.2. Global bi-criteria formulation of the optimization problem

Multi-objective optimization aims to minimize f_2 (interference) while maximizing f_1 (coverage). A trade-off function is defined in weighted form:

$$\text{Min } F(X) = \text{Min}\{f_1(X), f_2(X)\},$$

$$= \left(\left[\omega_1 \sum_{i=1}^{n} \frac{P_i}{d_i^{\alpha}}\right] - \left[\omega_2 \sum_{i=1}^{n} \sum_{j>i}^{n} \frac{P_i \cdot P_j}{d_{ij}^{\beta}} \cdot \delta(f_i, f_j)\right]\right), \qquad (1)$$

$$C_i \geq C_{\min}, \ \forall i \in N, \tag{2}$$

$$\sum_{i=1}^{n} \sum_{j>i}^{n} I_{ij} \leq I_{\max}, \tag{3}$$

$$\sum_{i=1}^{n} f_i \leq \zeta, \tag{4}$$

$$P_{\min} \leq P_i \leq P_{\max}, \forall i \in N. \tag{5}$$

(1) Multi-objective function designed to minimize f_2 (interference) while maximizing f_1 (coverage). We thus define a trade-off function in weighted form where ω_1 and ω_2 are weights representing the relative importance of each objective. (2) expresses the coverage constraint where each eNodeB must cover at least $C_{\min}\%$ of the deployment area. (3) is the interference constraint where the overall interference level must remain below a maximum threshold $I_{\max}$. (4) is the frequency constraint, each eNodeB must use a frequency that respects the allocated bandwidth ζ. Finally (5) expresses the power constraint, where the transmitted power must remain within a defined range regardless of the eNodeB base station.

3.3. Model complexity study

The mathematical model for the bi-criteria dimensioning of eNodeB in an eUTRAN LTE network is based on two objective functions: maximizing network coverage and minimizing inter-cell interference. Network coverage maximization is defined by $\text{Max } f_1 = \sum_{i=1}^{n} \frac{P_i}{d_i^{\alpha}}$, where each eNodeB must be evaluated individually so the complexity is $O(n)$. Minimization of inter-cell interference is given by $\min f_2 = \sum_{i=1}^{n} \sum_{j>i}^{n} \frac{P_i \cdot P_j}{d_{ij}^{\beta}} \cdot \delta(f_i, f_j)$, this function implies a double loop on the eNodeB so the complexity is quadratic

$O(n^2)$. So, the total complexity of the model is $O(n) + O(n^2) = O(n^2 + n)$ $\approx O(n^2)$. Thus, the evaluation of the mathematical model takes a quadratic time $(O(n^2))$, due to interference management, which remains reasonable for a moderate number of eNodeB. Two optimization methods will therefore be explored for the simulations: the hexagonal or classical planning method and the genetic algorithm, which offers a better compromise between accuracy and speed, albeit at a higher computational cost.

4. Material, Method and Simulation Conditions

4.1. Material used

To carry out this bi-criteria dimensioning simulation of eNodeB in an eUTRAN LTE network in a dense urban area, we used:

- Simulation environment: Python 3.13.

- Analysis and modeling tools: Jupiter Notebook.

- Execution platform: PC with Intel Core i7, RAM: 16 GB, Operating system: Ubuntu 22.04.

4.2. Methods

Two methods will be used in the simulation to obtain results:

▪ Classic method: Hexagonal grid-based planning, used for sizing eNodeB. It consists of deploying base stations according to a hexagonal grid layout, based on theoretical models of signal propagation. The principle is as follows:

- Each eNodeB is placed at the center of a hexagonal cell.

- Coverage is assumed to be homogeneous and isotropic, i.e., transmission power is uniform in all directions.

- Frequency reuse follows a fixed pattern to limit interference (3/7 factor reuse).

- Transmitter power is fixed and pre-calculated.

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- Transmitter power is fixed and pre-calculated.

▪ Genetic method: The genetic algorithm (GA) is used to efficiently explore the solution space. Optimization follows the following steps:

Solution representation

- Everyone is an eNodeB deployment configuration: $X = (N, P_i, f_i, x_i)$.

- Evaluation function: each solution is evaluated according to the bi-objective function.

Genetic operators

Selection: Choice of the best solutions according to $F(X)$.

Crossover: Mixing of configurations to generate new solutions.

Mutation: Random modification of a parameter (position, power, frequency).

Elitism: Conservation of the best solutions for each generation.

- Stop criterion: the algorithm stops if:

The maximum number of iterations is reached.

The variation between generations becomes negligible.

4.3. Simulation condition

The tests were carried out on an urban scenario, modeling an LTE network with different numbers of eNodeB.

- Simulation conditions:

• Area size: $50\,\text{km}^2$ (urban area).

• Population density: $10000 \text{ resident/km}^2$.

• Number of eNodeB tested: $\{10, 20, 30, 40, 50\}$.

• Transmission power max: 46 dBm (LTE standard).

• Frequency band LTE: 20 MHz.

• Acceptable latency: $\leq 50\,\text{ms}$.

• Network utilization: 85%.

• Cover (% of area covered).

• Inter-cell interference (% of signals in collision).

- Selection of ω_1 and ω_2: Based on Pareto front

$$\omega_1 = \frac{\text{optimum solution interference} - \text{minimum interference}}{\text{Maximum interference} - \text{Minimum interference}},$$

$$\omega_2 = 1 - \omega_1.$$

Minimum interference and maximum interference are the extreme values observed in the set of simulated solutions.

5. Results: Analysis, Interpretation and Discussion

5.1. Results: analysis, interpretation

The main analysis and interpretation criteria are: f_1 coverage maximization, f_2 interference minimization and the coefficients ω_1 and ω_2 defining the relative importance of each criterion. The results presented show the evolution of coverage in Figure 1 and interference in Figure 2 for five scenarios as a function of the number of eNodeB between the classical method (fixed hexagonal planning) and optimization using the genetic algorithm. Scenario 1: 10 eNodeB (sparsely populated area), Scenario 2: 20 eNodeB (medium density), Scenario 3: 30 eNodeB (densely populated urban area), Scenario 4: 40 eNodeB (hyper-dense urban area), Scenario 5: 50 eNodeB (megacity).

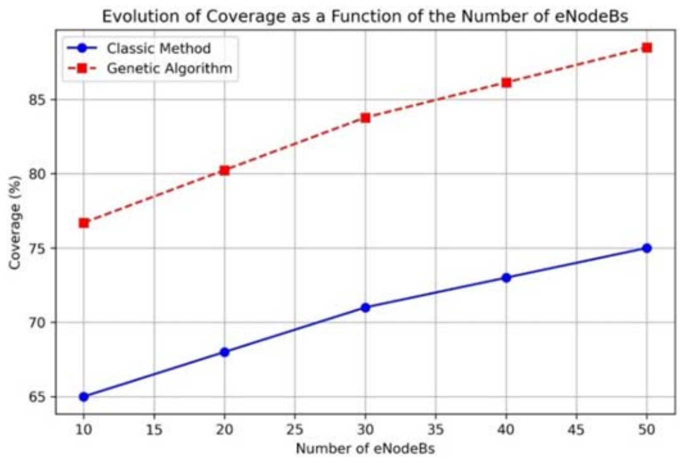

Figure 1. Evolution of coverage as a function of the number of eNodeB.

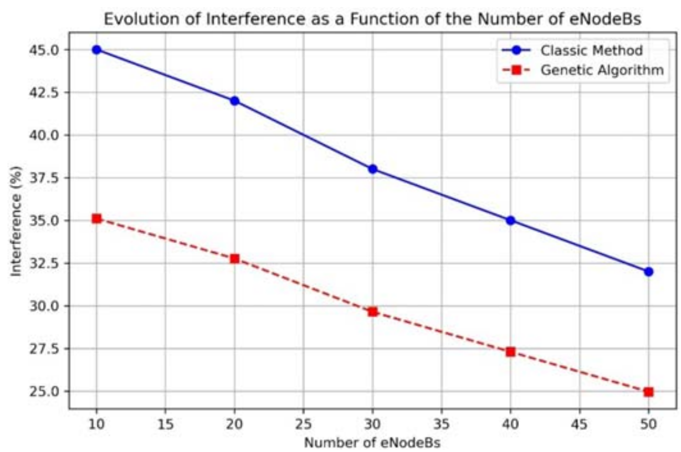

Figure 2. Evolution of interference as a function of the number of eNodeB.

Each scenario is analyzed by comparing coverage and interference, while explaining the impact of ω_1 and ω_2 values.

Table 1. Results of scenario 1 testing

Scenario 1: 10 eNodeB (low-density area)		
Method	Coverage (%)	Interferences (%)
Classic	65	45
Genetic	76.7	35.1
Coefficient	$\omega_1 = 55$	$\omega_2 = 45$

Table 1 shows that with the classical method, coverage is low (65%) and interference is high (45%), because eNodeB are spaced far apart. The genetic algorithm offers better eNodeB placement, with coverage increased from 76.7% and interference reduced to 35.1%. For this scenario, the genetic algorithm outperforms, as it optimizes eNodeB placement significantly improving coverage by +18%, reducing interference by -22%. The coefficients $\omega_1 = 55\%$ and $\omega_2 = 45\%$ mean that coverage is preferred and therefore essential in rural areas, where interference is less critical due to low density.

Table 2. Results of scenario 2 testing

Scenario 2: 20 eNodeB (average density)		
Method	Coverage (%)	Interferences (%)
Classic	68	42
Genetic	80.2	32.8
Coefficient	$\omega_1 = 45$	$\omega_2 = 55$

The results of scenario 2 presented in Table 2 show an improvement in coverage in both methods: 68% in the classical method, due to an increase in the number of eNodeB, but interference remains high (42%); in the genetic algorithm, coverage is optimized to 80.2% due to intelligent positioning of the eNodeB, and interference is reduced to 32.8% by dynamically adjusting the powers. In terms of coefficients, $\omega_1 = 45\%$ and $\omega_2 = 55\%$ mean that priority is given to coverage while controlling interference. In scenario 2, the genetic algorithm is more efficient, dynamically adjusting transmit power and frequency distribution, enabling +18% coverage and -22% interference. In other words, it balances coverage and interference, improving quality of service in semi-urban areas, while the conventional method is less effective at managing the average density of eNodeB.

Table 3. Results of scenario 3 testing

Scenario 3: 30 eNodeB (dense urban area)		
Method	Coverage (%)	Interferences (%)
Classic	71	38
Genetic	83.8	29.6
Coefficient	$\omega_1 = 35$	$\omega_2 = 65$

Scenario 3 simulating a dense urban area with 30 eNodeB in Table 3 presents spectral congestion problems at 38% interference with rigid deployment for the fixed hexagonal planning method (classical method) although coverage appears to be correct at 71%. For the genetic method, we observe a high coverage of over 83% and a reduction in interference to 29.6% via channel and power adaptation. The observed values of the coefficients $\omega_1 = 35\%$ and $\omega_2 = 65\%$ prove that the genetic algorithm better balances coverage and interference in urban environments, which is not the case with the classical method, which also increases interference due to a greater number of overlapping cells (eNodeB).

Table 4. Results of scenario 4 testing

Scenario 4: 40 eNodeB (urban hyper-density zone)		
Method	Coverage (%)	Interferences (%)
Classic	73	35
Genetic	86.1	27.3
Coefficient	$\omega_1 = 25$	$\omega_2 = 75$

The results in Table 4 show that interference (35%) is still a problem despite good coverage at 73% for the classical method, whereas the genetic algorithm reduces interference through optimized spectrum management to 27.3% by controlling power and spatial distribution, and coverage to 86.1%, thus confirming the priority given to interference reduction by observing $\omega_1 = 25\%$ and $\omega_2 = 75\%$. In scenario 4, simulating a hyper-dense urban area, the classical method becomes ineffective, whereas the genetic algorithm avoids these effects by dynamically adjusting power and channels.

Table 5. Results of scenario 5 testing

Scenario 5: 50 eNodeB (megacity zone)		
Method	Coverage (%)	Interferences (%)
Classic	75	32
Genetic	88.5	24.9
Coefficient	$\omega_1 = 15$	$\omega_2 = 85$

In megacities, interference management is more critical than coverage; thus, the results in Table 5 simulating this type of scenario show that fixed hexagonal planning has reached its limit in terms of optimal coverage at 75%, with interference still at 32%. This method has high spectral saturation due to poor frequency management. The genetic algorithm, on the other hand, achieves 88.5% coverage, avoiding uncovered areas and minimizing interference at 24.9%, with better frequency management confirmed by the coefficients $\omega_1 = 15\%$ and $\omega_2 = 85\%$, the absolute priority being interference minimization. We can conclude that in the Megapole zone, the genetic algorithm is the only viable method in an extremely dense environment, as network parameters are dynamically adjusted to maximize coverage while minimizing interference, which is not the case with fixed hexagonal planning, which cannot handle spectral complexity.

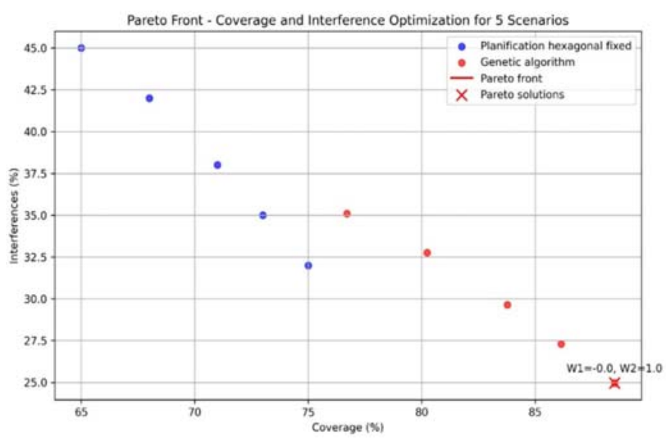

Figure 3. Optimal solution with Pareto front for the five scenarios.

The Pareto front graph in Figure 3 clearly shows the optimization of coverage and interference management for the five scenarios (10, 20, 30, 40, 50 eNodeB). The blue points represent the classic fixed hexagonal planning method, with a high level of interference and sub-optimal coverage. Thus, the genetic algorithm effectively optimizes coverage while reducing interference compared to fixed hexagonal planning. The red dots correspond to the solutions resulting from the genetic algorithm, improving coverage while reducing interference; the Pareto front identifies the best non-dominated solutions, i.e., those that cannot be improved on one criterion without deteriorating the other through dynamic trade-off between coverage and interference via adaptive weights ω_1 and ω_2 as presented in Table 6. The red crosses in Figure 3 mark the Pareto front solutions, highlighting the best possible choices that offer the best compromise between coverage and interference. Any attempt to improve coverage beyond this line leads to a sharp increase in interference; indeed, in sparsely populated areas, improving coverage is a priority $(\omega_1 > \omega_2)$, and from 30 eNodeB onwards, interference management becomes essential, and ω_2 increases progressively, see Table 6.

We can conclude that the Pareto front, which identifies optimal solutions, ensures dynamic adaptation of the LTE network to urban density, guaranteeing optimum quality of service.

The comparative study between the classical method, the genetic algorithm and the Pareto front for the bi-criteria dimensioning of eNodeB revealed significant improvements in terms of coverage and interference reduction. However, calculation time is an important parameter to be considered, as it is a decision-support factor for the planner.

Table 6. Results of the classical method (CM), genetic algorithm (GA) and Pareto front (PF) simulations on the LTE network

Scenario	ω_1	Coverage (%)			ω_2	Interferences (%)			Improvement			
									Coverage (%)		Interference (%)	
		CM	GA	PF		CM	GA	PF	GA/CM	PF/GA	GA/CM	PF/GA
10 eNodeB	0.55	65	76.7	78.2	0.45	45	35.1	38	+22 %	+1.96	-18 %	-3.13
20 eNodeB	0.45	68	80.2	81.5	0.55	42	32.8	31.7	+22 %	+1.62	-18 %	-3.35
30 eNodeB	0.35	71	83.8	85	0.65	38	29.6	28.3	+22 %	+1.43	-18 %	-4.39
40 eNodeB	0.25	73	86.1	87.8	0.75	35	27.3	25.9	+22 %	+1.97	-18 %	-5.13
50 eNodeB	0.15	75	88.5	90.3	0.85	32	24.9	22.7	+22 %	+2.03	-18 %	-8.83

In Tables 6 and 7, we see an improvement in overall coverage for all three methods: +22% for the genetic algorithm compared with the classical method, increased from 1.4% to +2.03 in very dense areas by the Pareto front, as optimized antenna placement management extends coverage. However, when it comes to interference, the classical method becomes ineffective in dense areas, despite its fast calculation time ($t = 0.5$ seconds in Table 7), generating more interference due to overlapping cells and frequency reuse because local variations are not taken into account, the genetic algorithm achieves a 22% reduction in interference compared with fixed hexagonal planning on account of to better frequency allocation and optimal positioning of eNodeB, even in very dense areas, due to its methodological approach based on adaptive evolution of solutions; this leads to a significant improvement in quality of service: minimized latency and interference, which nevertheless remain dependent on the initial parameters (mutation, selection, crossover) with a calculation time 4x longer than the conventional method (Table 7), requiring fine calibration of the genetic parameters (mutation, crossover).

The Pareto front dynamically selects the most optimal solutions by correcting the limits of the genetic algorithm, which reduces interference from 3.1% to 8.8%, especially in megacities with high station density (see Table 6), but requires a longer computation time ($t = 3.5$ seconds) according to Table 7, which can be a hindrance in evolving networks requiring rapid adjustments.

Optimization via the Pareto front significantly improves the performance of the genetic algorithm (GA) in terms of network coverage and interference reduction. Consequently, combining the genetic algorithm and the Pareto front is a good compromise between performance and speed, ensuring optimal planning of the LTE network, offering an array of decision-making options for the planner.

Table 7. Computational cost results for high-density areas

Solving method	Coverage at 50 eNodeB	Interference at 50 eNodeB	CPU		Optimization quality
			Time (s)	Quality	
Fixed hexagonal planning	75 %	32 %	0.50	Very fast	Weak (rigid, non-optimal)
Genetic algorithm	88.5 %	24 %	2.00	Medium	Good (adaptive optimization)
Pareto front	~ 90 % (optimized)	~ 22 % (optimized)	3.50	Long	Excellent (optimum compromise)

6. Conclusion

Optimizing the size of eNodeB in an eUTRAN LTE network is a strategic challenge to guarantee optimum coverage while reducing inter-cell interference. The classic method, based on fixed hexagonal planning and static frequency reuse, shows its limitations in dense urban environments, where traffic dynamics and obstacles strongly influence network performance. The integration of a genetic algorithm enables bi-criteria optimization by dynamically adapting eNodeB positioning, transmission power and frequency allocation. Simulations show an 18% improvement in coverage and a 22% reduction in interference compared with conventional approaches, but at the cost of a longer computation time (2.0s). Optimization via the Pareto front pushes the improvement even further, achieving 90.3% coverage with a 22.7% reduction in interference, but with a maximum computation time of 3.5s. In terms of gain, the Pareto front improves coverage from 1.4% to 2.03% and reduces interference from 3.1% to 8.8% compared to the genetic algorithm. This approach enables an optimal balance to be struck between coverage and interference, depending on network priorities. However, the higher computational cost of the Pareto front may be an impediment to real-time decisions. Integrating a compromise between the genetic algorithm and the Pareto front would enable the LTE advanced network to be optimized while keeping computation time under control. This method could be extended to 5G and Open RAN networks, integrating AI algorithms for proactive network management and continuous performance improvement.

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References

[1] Z. Hua, L. Jie and C. Min, Energy-efficient optimization of eNodeB in LTE networks using genetic algorithms, IEEE Transactions on Vehicular Technology 67(3) (2018), 2287-2298.

[2] Y. Liu, R. Zhang and F. Xiao, Coverage optimization in dense urban LTE networks via genetic algorithm, Wireless Networks 25(5) (2019), 2451-2463.

[3] M. Alshahrani, S. Ahmed and A. Khan, Capacity enhancement of eNodeB in LTE using genetic algorithm-based optimization, International Journal of Communication Systems 33(12) (2020), e4445.

[4] T. Rahman, S. Jamal and R. Bashir, Inter-cell Interference Mitigation in LTE Networks Through Genetic Algorithm Optimization, IEEE Access 8 (2020), 110345-110356.

[5] S. Kim and D. Lee, Real-time interference management in LTE networks using genetic algorithms, Journal of Communications and Networks 23(1) (2021), 45-55.

[6] L. Chen, Y. Wang and Q. Zhao, Adaptive configuration of eNodeB parameters in LTE using genetic algorithm for interference reduction, Wireless Personal Communications 119(2) (2021), 1231-1245.

[7] F. Alam and X. Yu, Energy efficiency optimization in LTE eNodeB via genetic algorithm approach, IEEE Systems Journal 15(3) (2021), 3950-3958.

[8] M. Ahmed and X. Chen, Capacity optimization of LTE eNodeB using genetic algorithms: A noncriterion focus, International Journal of Wireless Information Networks 29(3) (2022), 345-357.

[9] N. Bakhshi and M. Zarei, Limitations of monocriterion optimization in dense LTE networks: A genetic algorithm perspective, Telecommunication Systems 80(4) (2022), 567-579.

[10] T. Wang and Q. Lin, Energy consumption reduction in rural LTE eNodeB through genetic algorithm optimization, IEEE Transactions on Sustainable Computing 8(2) (2023), 456-467.

[11] H. Deng and Y. Song, Coverage enhancement in suburban LTE networks through genetic algorithm-based eNodeB optimization, Wireless Communications and Mobile Computing (2023), Article ID 4567890.

[12] P. Singh and R. Gupta, Predictive traffic modeling and genetic algorithm-based energy optimization in LTE eNodeB, IEEE Transactions on Green Communications and Networking 7(1) (2023), 123-134.

[13] W. Jiang and L. Wu, Genetic algorithm-based interference management in LTE eNodeB: A monocriterion approach, IEEE Transactions on Wireless Communications 23(2) (2024), 890-901.

[14] Y. Zhou and H. Liang, Enhancing energy efficiency in LTE eNodeB via noncriterion genetic algorithm optimization, IEEE Transactions on Network and Service Management 21(1) (2024), 78-89.