Hybrid AI-Assisted EM and GIS Framework for Radio Parameter Optimization in Dense Urban Cellular Networks

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Original scientific article

***Abstract*—Optimizing antenna parameters is essential to improve coverage and quality of service in wireless cellular networks. Electrical tilt and azimuth strongly influence the Reference Signal Received Power (RSRP) and the Signal-to-Interference-plus-Noise Ratio (SINR), which are key Quality of Service (QoS) indicators. Conventional approaches, based on field measurements and manual tuning, are costly and inefficient in dynamic urban environments. To overcome these limitations, this paper proposes a hybrid framework integrating a high-fidelity electromagnetic simulator and a Geographic Information System to realistically model radio propagation and accurately evaluate performance. The optimization targets electrical tilt—remotely adjustable via the Remote Electrical Tilt (RET) mechanism—as well as azimuth, which requires on-site reconfiguration. The search relies on advanced metaheuristics, namely Genetic Algorithms and Artificial Immune Systems, ensuring efficient exploration and robust convergence. Experiments conducted on the LTE-Advanced network of Algeria Telecom Mobile – Mobilis in Oran demonstrate performance gains of up to 23% in the fitness function, which combines an average RSRP greater than -85 dBm and an average SINR greater than 10 dB, compared to the operator's configurations obtained through manual optimization based on drive tests. These results confirm the effectiveness of the proposed approach for optimizing antenna parameters in complex urban environments. Beyond performance gains, the proposed framework reduces operational costs and is compatible with Self-Organizing Networks (SON) and RET systems, providing a scalable solution for current and future cellular networks in large-scale Internet of Things (IoT) scenarios.**

***Index Terms*—Cellular Networks, Radio Network Optimization, Hybrid Optimization Approaches, Artificial Intelligence, Metaheuristics, Geographic Information System, Radio Performance, Long Term Evolution–Advanced, Fifth Generation, Internet of Things.**

I. INTRODUCTION

THE rapid growth of the Internet of Things (IoT) and emerging services such as massive machine-type communications (mMTC), Industrial IoT (IIoT), autonomous vehicles, and augmented/virtual reality (AR/VR) imposes unprecedented demands on next-generation cellular networks in terms of coverage, reliability, and Quality of Service (QoS) [1], [2]. In dense urban areas, radio propagation is strongly affected by building morphology, obstacles, and user distribution, making antenna parameter tuning a critical task [3], [4].

Among these parameters, electrical tilt and azimuth play a central role in maintaining homogeneous coverage and limiting interference. Antenna tilt and azimuth are critical factors in determining the overall QoS of cellular networks, as they govern the vertical and horizontal distribution of the radiated beam, directly influencing the Reference Signal Received Power (RSRP), the Signal-to-Interference-plus-Noise Ratio (SINR), coverage continuity, and inter-cell interference levels. In dense Long Term Evolution (LTE)-Advanced and Fifth-Generation (5G) deployments, even small configuration inaccuracies can lead to coverage gaps, degraded user experience, and inefficient spectrum utilization, making their optimization essential for enhancing capacity and improving interference management [5], [6].

In practice, electrical tilt can be remotely adjusted through Remote Electrical Tilt (RET) mechanisms integrated into evolved Node B (eNodeB) / next-generation Node B (gNodeB) equipment or Operations Support System (OSS) platforms [7], [8], often combined with Self-Organizing Network (SON) and centralized SON (C-SON) functions for automated optimization [9], [10]. In contrast, azimuth adjustment requires on-site mechanical intervention, resulting in longer delays and higher operational costs [11].

Traditional optimization relies on drive-test campaigns where performance indicators are collected along predefined routes and analyzed with Geographic Information System (GIS)-based tools (e.g., Atoll, MapInfo) to identify coverage gaps and update configurations [12], [13]. While effective, this process is costly, slow, and poorly suited for dynamic environments [12], [14]. In dense LTE-Advanced and 5G deployments, the limitations are even more severe: a single campaign rarely ensures complete coverage, traffic dynamics quickly render measurements obsolete, and manual analysis cannot efficiently capture inter-cell interactions.

To overcome these limitations, several recent studies have introduced metaheuristic algorithms and Artificial Intelligence (AI) into SON and RET optimization loops [15]. Genetic Algorithms (GA) and Artificial Immune Systems (AIS) have

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demonstrated strong capabilities in exploring large solution spaces while maintaining stable convergence behavior [16], [17]. Complementarily, AI-based techniques can process extensive network datasets and capture complex radio interactions, providing enhanced decision-making and adaptation capabilities in dense urban scenarios [18].

Despite these advances, optimizing antenna parameters in dense urban cellular environments remains a complex and multidimensional challenge. Drive-test campaigns, traditionally used to identify low-performance areas, remain costly, time-consuming, and insufficiently responsive to rapidly changing radio conditions and traffic dynamics [12], [14]. In LTE-Advanced and 5G networks, where site density is high and inter-cell interactions become increasingly complex, these methods prove progressively less suitable, as they fail to capture the full spatio-temporal variability of the radio channel [18], [19]. AI-based approaches offer promising adaptation and automation capabilities, but they require large and representative datasets and often lack robustness when applied to heterogeneous geographical or topographical environments [20]. In parallel, metaheuristic methods enable efficient exploration of large solution spaces, yet they are still rarely combined with realistic propagation models that integrate both high-fidelity electromagnetic (EM) simulations and detailed GIS information—elements that are essential for accurate performance evaluation [21]. Moreover, multi-parameter optimization, although highly promising, typically leads to significant computational cost and long convergence times, which hinder its applicability in SON systems requiring near real-time decision-making [9].

These limitations motivate the adoption of a single-parameter optimization strategy in which electrical tilt and azimuth are treated independently. This separation allows for more precise control over the impact of each configuration adjustment, reduces search complexity, and aligns with the operational distinction between remotely adjustable parameters (RET) and those requiring mechanical intervention.

In this work, we propose a hybrid framework combining EM simulation, GIS data, and metaheuristic algorithms (GA and AIS) to optimize a single antenna parameter—either electrical tilt or azimuth—depending on operational requirements. The problem is formulated as a multi-objective optimization aiming to maximize coverage uniformity while reducing interference. Integration into SON/RET environments enables full automation of tilt optimization and provides reliable decision-support for azimuth adjustments.

To further reinforce the originality of the proposed method, the joint use of high-fidelity EM simulation, detailed GIS data, and AI-oriented techniques provides a realistic representation of the radio environment while accounting for site-specific characteristics such as topography, built density, street orientation, and obstacles. This enhanced modeling enables a more accurate evaluation of each antenna configuration and yields operator-ready optimization outcomes that overcome the limitations of simplified or statistically approximated propagation models.

The framework is validated on a commercial LTE-Advanced network in Oran, Algeria, operated by Algeria Telecom Mobile – Mobilis (ATM Mobilis). This dense urban area, characterized by complex topography and heterogeneous traffic, provides a representative testbed. Results demonstrate significant improvements in coverage and signal quality while reducing operational costs and reconfiguration delays.

This work introduces several original contributions, detailed as follows:

- The development of a hybrid optimization framework combining AI metaheuristics with a high-fidelity EM simulator integrated into a GIS, enabling realistic modeling of radio propagation in dense urban environments.
- The use of real databases, including physical radio parameters configured by the operator ATM Mobilis and topographical terrain characteristics, ensuring that the EM simulation accurately reflects real-world site conditions.
- The design of an integrated fitness function combining the maximization of coverage and the improvement of received signal quality—namely RSRP and SINR, ensuring an optimal trade-off between service area extension and signal strength.
- The implementation of a single-parameter optimization strategy, applied separately to electrical tilt and azimuth, to enhance both coverage and QoS while minimizing inter-cell interference.
- A comparative analysis of the performance of GA and AIS algorithms applied to antenna parameter optimization, highlighting their complementarity and showing performance gains of up to 24% compared to the operator's initial configurations.

The remainder of this paper is organized as follows: Section II reviews related works, Section III presents the proposed hybrid framework, Section IV discusses the Oran case study and results, and Section VI concludes the paper with the main contributions and research perspectives.

II. Related Work

Manual optimization based on drive tests has long been the standard approach used by mobile operators for tuning radio parameters such as azimuth, tilt, and transmission power. Although effective for on-site diagnosis, this approach remains costly, time-consuming, non-scalable, and unsuitable for dynamic urban environments where radio conditions evolve rapidly [13], [11]. These limitations have motivated the development of automated, data-driven, and AI-based optimization methods capable of providing continuous and adaptive parameter tuning.

With the increasing complexity of 5G and emerging 6G networks, artificial intelligence techniques have become central to cellular network optimization. Statistical learning models, deep neural networks, fuzzy logic, and federated learning have been employed to capture nonlinear relationships between radio parameters and QoS indicators [21], [20]. Reinforcement learning, including Q-learning and Deep Q-Networks, has demonstrated strong potential for dynamic RET optimization by adaptively responding to spatio-temporal traffic variations [22], [8]. Furthermore, recent studies on massive MIMO highlight advanced AI-driven solutions for pilot contamination mitigation and intelligent beamforming in B5G/6G systems [2].

Metaheuristic algorithms represent another major research direction. GA, PSO, DE, AIS, and hybrid strategies have been widely investigated for optimizing antenna orientation, tilt, power allocation, or site placement [23], [24], [26], [27]. In particular, self-adaptive mutation genetic algorithms have demonstrated significant improvements in 5G coverage optimization when combined with calibrated propagation models derived from field measurements [1]. The integration of metaheuristics with high-resolution GIS data or high-fidelity EM simulators has also yielded notable performance gains by providing more realistic propagation modeling [15], [25].

Azimuth optimization has been addressed through case-based reasoning, Radio Environment Maps, and evolutionary algorithms, enabling performance improvements beyond operators' empirical configurations [33], [29]. Joint tilt–azimuth optimization has shown superior performance in terms of coverage enhancement and inter-cell interference reduction, especially in dense urban scenarios [31]. Nevertheless, azimuth tuning still requires mechanical intervention, making it less compatible with fully autonomous SON mechanisms.

Electrical tilt (RET) remains a critical parameter for controlling coverage footprint and interference. Several works emphasize its strong impact on received signal quality in dense urban environments [3], [4]. Machine-learning-based modeling, Bayesian approaches, and AIS-inspired optimization methods have been explored to overcome the limitations of manual tilt tuning [28]. Recent off-policy reinforcement learning solutions for RET optimization further highlight the effectiveness of model-driven learning in heterogeneous configurations [8].

Propagation modeling accuracy is a key factor influencing the success of antenna-parameter optimization. Simplified empirical models often fail to capture the complexity of diffraction, shadowing, or multipath reflections in urban environments. Thus, the literature increasingly promotes the use of high-resolution GIS layers, DTM/DSM datasets, and 3D EM simulations to improve prediction fidelity [14], [15], [19]. These techniques have proven particularly beneficial for 5G deployments in dense cities, where fine-grained adaptation of antenna parameters to architectural and topographic constraints is essential.

Finally, the emergence of Smart Radio Environments (SRE) leveraging Reconfigurable Intelligent Surfaces (RIS) and Network-Controlled Repeaters (NCR) opens new perspectives for 6G networks. Deep reinforcement learning applied to RIS-assisted communication enables substantial improvements in coverage, capacity, and physical-layer security [34], [35], [36], [37]. Optimal planning methods for heterogeneous smart radio environments further confirm the strategic importance of intelligent metasurfaces in next-generation networks [5], [32].

To provide a more structured overview of the existing literature, a summary table of the main contributions and methodological orientations has been added (see Table I).

TABLE I
SUMMARY OF KEY RESEARCH DIRECTIONS IN LTE-A, 5G, AND 6G RADIO-PARAMETER OPTIMIZATION.

Category	Approaches	Main Contributions	Refs.
Manual optim.	Drive tests, empirical tuning	Reliable field-based adjustment; baseline operator practice	[13], [11]
AI/ML-based	RL, DNNs, FL, fuzzy logic	Dynamic RET control, KPI prediction, improved QoS	[20], [21], [22], [8], [2]
Metaheuristics	GA, PSO, DE, AIS	Tilt/azimuth optim., interference reduction, coverage gain	[1], [23], [24]
Azimuth optim.	CBR, REM, evol. algos	Coverage increase, reduced interference	[33], [29], [31]
Tilt (RET)	ML models, Bayesian, AIS, RL	Dynamic tilt, improved SINR, coverage shaping	[3], [4], [28]
Propagation modeling	GIS, 3D-EM, DTM/DSM	Accurate maps for dense urban scenarios	[14], [15], [19]
Smart Radio Env.	RIS, NCR, DRL	Coverage, capacity and secured links (5G/6G)	[34], [35], [36], [37], [5]

III. HYBRID AIS/GA–EM&GIS APPROACH

The proposed *Hybrid AIS/GA–EM&GIS framework* combines bio-inspired metaheuristics (AIS or GA) with an EM simulator integrated into a GIS. Its objective is to optimize antenna tilt or azimuth in dense urban environments, thereby enhancing both coverage and service quality.

The optimization process relies on iterative interaction between two modules (Fig. 1): an AI-based optimizer (AIS or GA) that generates candidate configurations, and the EM&GIS simulator that evaluates their performance. Each candidate is encoded into standardized input files and processed by the simulator. The EM engine models propagation phenomena such as reflection, diffraction, and terrain effects, while the GIS ensures geospatial consistency by incorporating elevation, building geometry, and vegetation data.

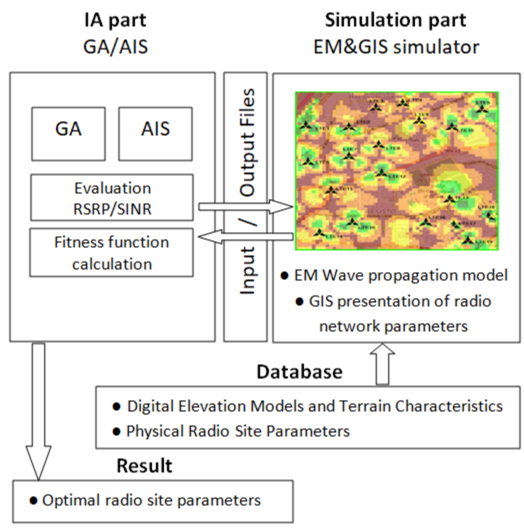


Fig. 1. Proposed Hybrid AIS/GA–EM&GIS Framework

Simulation outputs are used to compute two key radio metrics: RSRP and SINR. A single fitness function F is defined as:

$$F(\text{solution}_i) = T_i^{\text{RSRP}} \cdot T_i^{\text{SINR}} \quad (1)$$

where T_i^{RSRP} is the proportion of points with RSRP above -85 dBm, and T_i^{SINR} is the proportion of points with SINR greater than 10 dB. This formulation enforces both coverage and link-quality constraints. Fitness values are then reinjected into the optimizer to guide solution generation until convergence.

In a multi-site network, the search space grows exponentially. With k possible tilt or azimuth values per antenna and N sectors, the number of configurations is:

$$|ER| = k^N \quad (2)$$

with computational complexity:

$$\mathcal{O}(k^N \cdot C_F) \quad (3)$$

where C_F denotes the evaluation cost of a single configuration by the EM&GIS simulator. Exhaustive search is thus intractable for operational-scale networks. To address this, the framework leverages GA or AIS, which balance global exploration with local exploitation, enabling scalable and efficient optimization.

A. Bio-Inspired Metaheuristics

Bio-inspired metaheuristics constitute the core of the optimization module within the proposed AIS/GA–EM&GIS framework. They interact iteratively with the EM&GIS simulator: the optimizer generates candidate configurations, while the simulator provides accurate radio evaluations based on the RSRP and SINR metrics, ensuring an effective balance between global exploration and local exploitation.

Depending on the selected optimization type, each solution encodes a specific set of radio parameters:

- *Azimuth optimization:* admissible values range from 0° to 360°, with a typical operational step of 10°.
- *Tilt (RET) optimization:* the range depends on the antennas deployed in the study area and typically varies between –4° and +8°, with a step of 1°.

These parameters form the genes manipulated by the evolutionary algorithms.

In the case of Genetic Algorithms (GA), each solution is represented as a chromosome whose genes correspond to the physical parameters (tilt or azimuth) of the network sectors. Figure 2 illustrates this structure: a chromosome groups the parameter values associated with multiple sites, each composed of three sectors. This compact representation facilitates the application of genetic operators—selection, crossover, and mutation—allowing efficient exploration of the exponentially large search space.

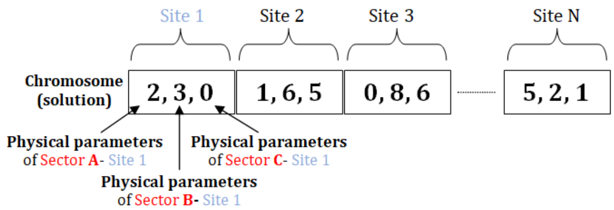


Fig. 2. Structure of a chromosome composed of several sites, each including three sectors, where each gene encodes a physical parameter (tilt or azimuth).

Artificial Immune Systems (AIS) rely on the clonal selection principle: each candidate solution is cloned proportionally to its performance and undergoes adaptive mutation. Poorly performing solutions receive stronger mutations to encourage exploration, whereas high-performing individuals undergo milder perturbations to refine their local search. This mechanism preserves diversity and prevents premature convergence, which is crucial for large-scale radio optimization problems.

For both approaches, the fitness function defined in 1 acts as the unique evaluation criterion guiding the evolution of solutions, ensuring joint optimization of coverage and link quality. This subsection therefore provides the necessary foundations for integrating the GA and AIS modules into the hybrid AIS/GA–EM&GIS framework, which is presented in the following subsection.

B. Hybrid GA–EM&GIS Approach

In the GA module, each solution is encoded as a chromosome whose genes represent tilt or azimuth parameters of the $N = 19$ sectors under study. The initial population contains $M = 25$ chromosomes.

Crossover is applied with probability $P_c = 0.7$, producing offspring by recombining parent characteristics. If not selected, parents are directly copied into the next generation, preserving strong solutions. Mutation occurs with probability $P_m = 0.02$, introducing random changes to maintain genetic diversity and avoid premature convergence.

C. Hybrid AIS–EM&GIS Approach

The AIS module applies clonal selection. Each candidate solution (antibody) is cloned proportionally to its fitness. Clones undergo adaptive mutation with rate:

$$M\_rate = \max\left(0.05,\ 0.1 \cdot \left(1 - \frac{F\_clone}{best\_F}\right)\right) \quad (4)$$

This rule enforces a minimum mutation rate of 0.05. Solutions far from the optimum receive stronger mutations to encourage exploration, while those near the optimum undergo lighter mutations for local refinement.

To preserve diversity, a pool of random individuals is injected at each generation, ensuring a balanced population of optimized clones, random candidates, and elite individuals from previous generations.

IV. Results and Discussion

The proposed Hybrid GA/AIS–EM&GIS framework was validated on a commercial LTE-Advanced network operated by ATM Mobilis in Oran, Algeria, located about 400 km west of Algiers. Oran presents a challenging radio environment characterized by high user density, compact urban morphology, and proximity to rugged coastal terrain and industrial zones. These factors amplify shadowing, multipath propagation, and inter-cell interference, making the city a representative testbed for evaluating optimization strategies (Fig. 3).

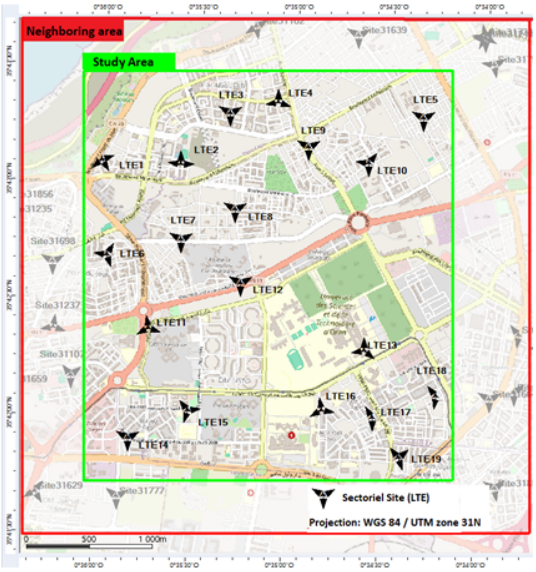


Fig. 3. Study area: Oran, Algeria.

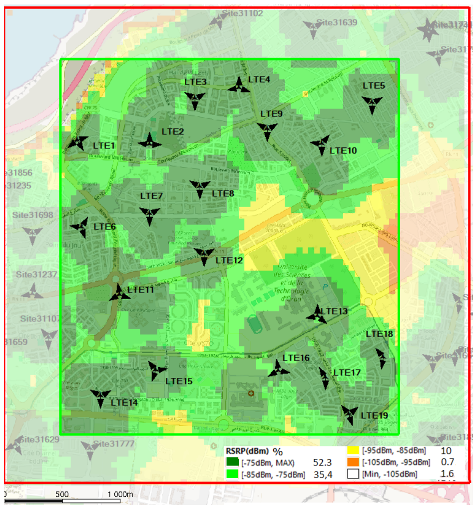
The network includes nineteen sites with three sectors each, totaling fifty-seven sectors. Operator-provided parameters—Global Positioning System coordinates, antenna heights, azimuth orientations, and electrical tilts—were combined with geospatial data such as a digital terrain model and detailed urban morphology. These inputs were integrated into the EM&GIS module to enable realistic propagation modeling.

Performance evaluation focused on two key metrics: RSRP, with a threshold of -85 dBm to characterize coverage, and SINR, with a threshold of 10 dB to capture link quality. These thresholds align with LTE-Advanced and 5G standards and provide reliable indicators of both signal availability and communication robustness.

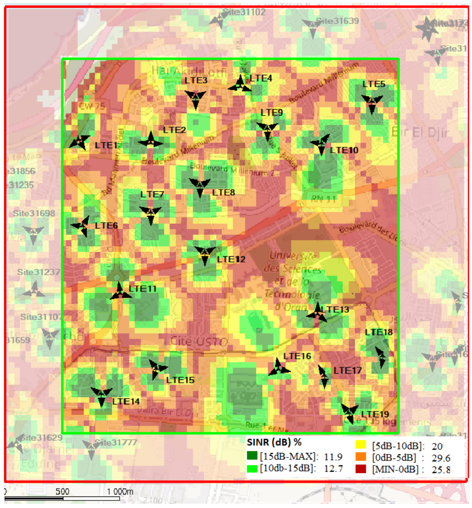
A. Operator Configuration

The baseline configuration corresponds to the parameters deployed by ATM Mobilis, including site locations, antenna heights, transmit powers, and tilt/azimuth settings determined through manual on-site adjustments. These values reflect the operator's operational practices in the study area.

As shown in Fig. 4, the operator's configuration achieves 87.7% coverage above –85 dBm and 24.6% of points above 10 dB SINR. This reflects a trade-off between maximizing coverage and limiting inter-cell interference in a dense urban setting.



(a) RSRP simulated by EM&GIS, 87.7% coverage ($\geq$ –85 dBm)



(b) SINR simulated by EM&GIS, 24.6% of points $\geq$ 10 dB

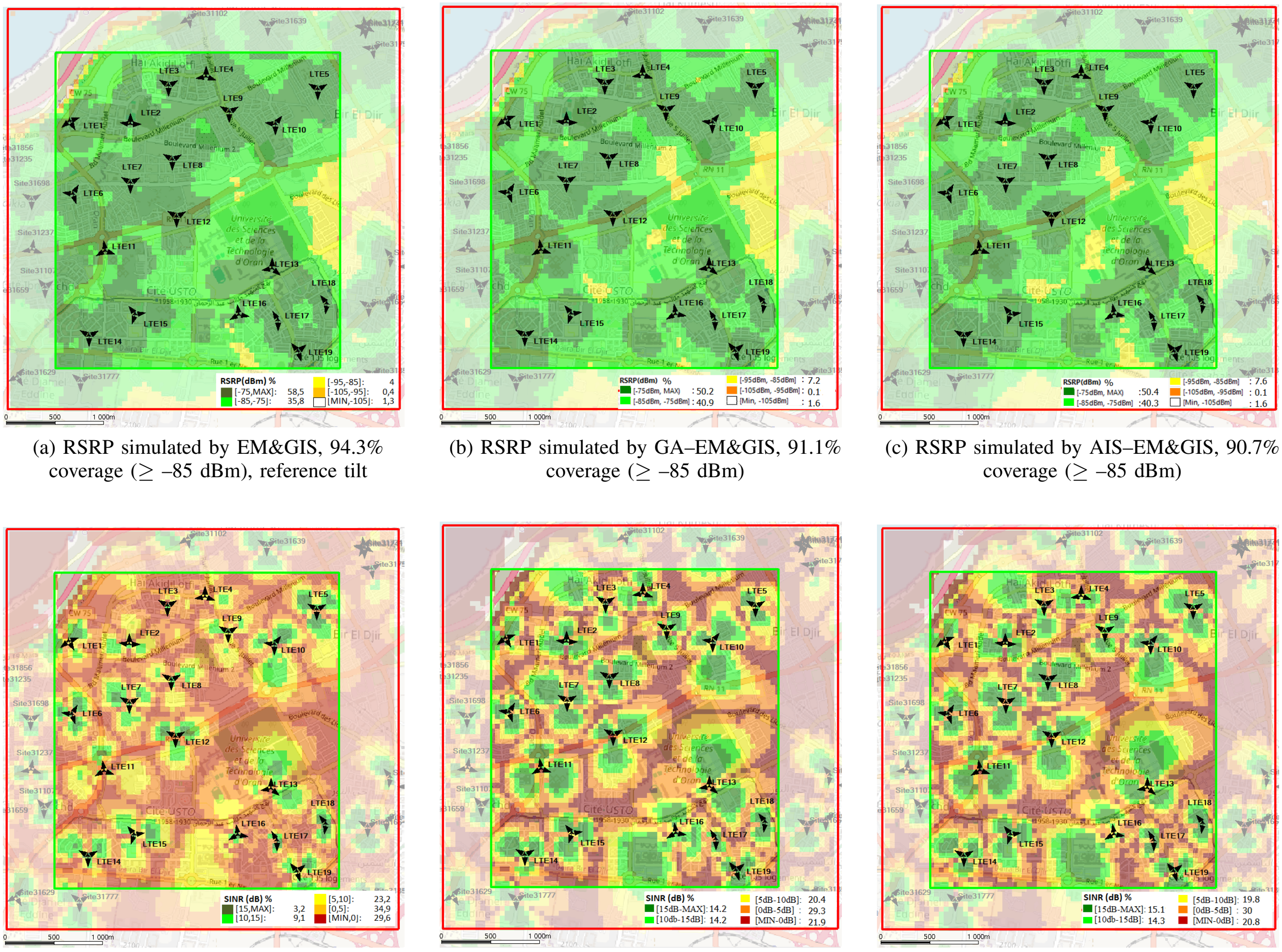
Fig. 4. RSRP and SINR maps for the operator's configuration, simulated using EM&GIS.

These results confirm that careful manual tilt adjustments can mitigate interference and improve signal quality. However, the process depends on extensive drive-test campaigns and KPI analysis, which are both costly and time-consuming. The proposed *Hybrid AIS/GA–EM&GIS* framework automates this process, enabling more efficient and scalable optimization.

B. Tilt Optimization

This subsection evaluates electrical tilt optimization while keeping azimuths fixed to the operator's baseline configuration. This setup isolates the direct impact of tilt adjustments on network performance, particularly RSRP and SINR.

Tilt optimization is inherently combinatorial. Each of the 57 sectors supports 13 tilt values (from –4° to +8° with 1° increments), yielding a search space of $13^{57} \approx 10^{63}$ configurations. Exhaustive search is thus infeasible, especially as each candidate requires EM&GIS-based RSRP and SINR evaluation.



(a) RSRP simulated by EM&GIS, 94.3% coverage (≥ –85 dBm), reference tilt

(b) RSRP simulated by GA–EM&GIS, 91.1% coverage (≥ –85 dBm)

(c) RSRP simulated by AIS–EM&GIS, 90.7% coverage (≥ –85 dBm)

(d) SINR simulated by EM&GIS, 12.3% of points ≥ 10 dB, reference tilt

(e) SINR simulated by GA–EM&GIS, 28.4% of points ≥ 10 dB

(f) SINR simulated by AIS–EM&GIS, 29.4% of points ≥ 10 dB

Fig. 5. RSRP and SINR maps for reference tilt (0°), GA, and AIS configurations with tilt-only optimization.

To address this challenge, two bio-inspired algorithms—GA–EM&GIS and AIS–EM&GIS—were applied. Each solution is represented as a 57-gene vector encoding tilt values. GA ensures global exploration through selection, crossover, and mutation, while AIS refines solutions locally via clonal selection and adaptive mutation.

Results show that the reference configuration (tilt = 0° with operator azimuths) achieves 94.3% of points above –85 dBm RSRP (Fig. 5a). Optimization with GA and AIS yields 91.1% and 90.7%, respectively (Figs. 5b, 5c), slightly reducing overall coverage but extending service to peripheral areas poorly served in the reference case.

For SINR, the baseline configuration achieves only 12.3% of points above 10 dB (Fig. 5d). Optimization with GA and AIS increases this to 28.4% and 29.4%, respectively (Figs. 5e, 5f), highlighting significant improvements in inter-cell interference management. AIS provides the best link quality, surpassing GA in interference reduction and signal enhancement.

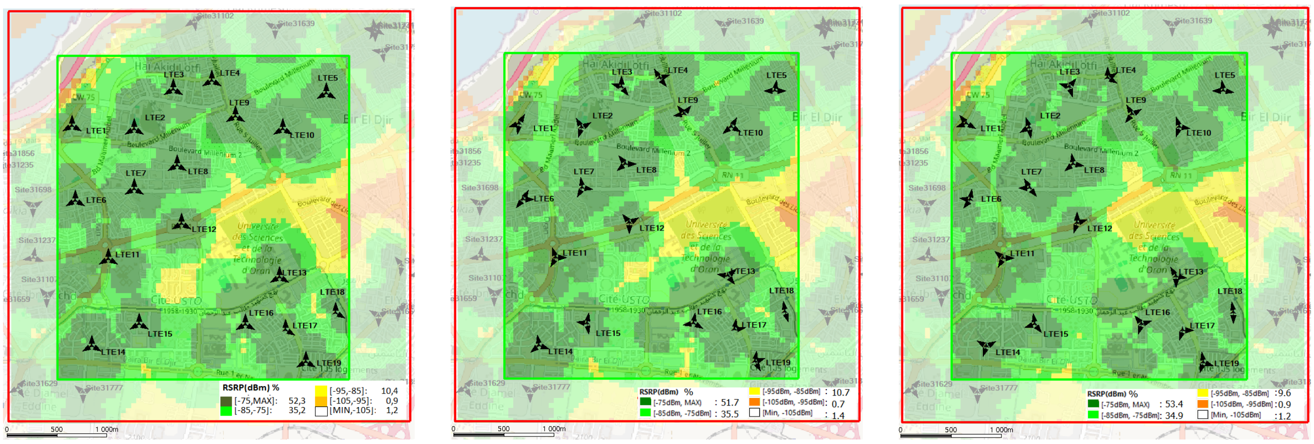
These results confirm that algorithmic tilt optimization improves both coverage distribution and radio quality relative to manual adjustments. GA favors coverage maximization, while AIS achieves superior SINR gains. The combination of EM&GIS propagation modeling with bio-inspired metaheuristics effectively addresses the large-scale combinatorial nature of tilt optimization, providing a robust foundation for hybrid optimization in dense networks.

C. Azimuth Optimization

This subsection evaluates antenna azimuth optimization, which modifies sector orientations while keeping tilt values fixed to the operator's configuration. Unlike tilt, which controls vertical inclination, azimuth directly affects horizontal coverage distribution and inter-cell interference.

Azimuth optimization is a highly combinatorial problem. Each sector supports 36 possible orientations, constrained by a minimum 60° separation between co-site sectors. For 57 sectors, the theoretical search space is 36^{57}, making exhaustive exploration intractable. Moreover, each candidate must be evaluated by EM&GIS, which is computationally expensive.

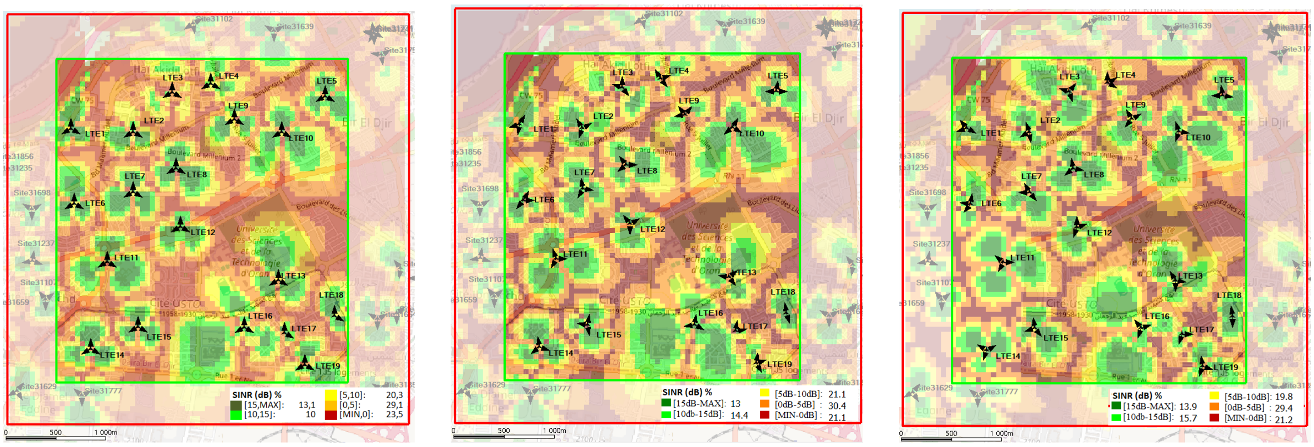
To overcome this challenge, GA–EM&GIS and AIS–EM&GIS were applied. Both algorithms iteratively interact with EM&GIS for fitness evaluation. Their complementary strengths—GA's exploratory ability and AIS's refinement ca-



(a) RSRP simulated by EM&GIS, 87.5% coverage (≥ –85 dBm), reference azimuth

(b) RSRP simulated by GA–EM&GIS, 87.2% coverage (≥ –85 dBm)

(c) RSRP simulated by AIS–EM&GIS, 88.3% coverage (≥ –85 dBm)



(d) SINR simulated by EM&GIS, 23.1% of points ≥ 10 dB, reference azimuth

(e) SINR simulated by GA–EM&GIS, 27.4% of points ≥ 10 dB

(f) SINR simulated by AIS–EM&GIS, 29.6% of points ≥ 10 dB

Fig. 6. RSRP and SINR maps for reference azimuth, GA, and AIS configurations with azimuth-only optimization.

pacity—make them suitable for large-scale azimuth optimization.

As shown in Fig. 6, azimuth optimization yields substantial performance gains over the reference. In terms of coverage, the operator configuration achieves 87.5% of points above –85 dBm (Fig. 6a). GA achieves 87.2% (Fig. 6b), while AIS improves coverage to 88.3% (Fig. 6c). For SINR, the reference yields 23.1% of points above 10 dB (Fig. 6d), compared to 27.4% for GA (Fig. 6e) and 29.6% for AIS (Fig. 6f).

Overall, AIS provides the best interference reduction and link quality, while GA slightly favors coverage. These results confirm that azimuth optimization with bio-inspired algorithms effectively handles the combinatorial complexity and significantly enhances network performance compared to static operator configurations.

V. Comparative Analysis and Optimization Results

The proposed GA/AIS–EM&GIS optimization framework was compared with the operator's manual configuration. The final optimized tilt and azimuth values for each site and sector are presented in Table II, while the global performance indicators are summarized in Table III. This dual analysis enables an accurate assessment of the contribution of bio-inspired algorithms to network improvement and their potential for operational deployment.

The reference configuration, derived from drive-test campaigns, achieves 87.7% coverage (RSRP ≥ -85 dBm) and 24.6% of points above the SINR threshold. While effective, this process is time- and resource-intensive.

For tilt optimization, the reference (tilt = 0°) provides high coverage (94.3%) but poor link quality (12.3%). GA–EM&GIS improves the fitness score by 19.9%, converging in 3,374 iterations (1h52min), while AIS–EM&GIS achieves a 23.6% gain with faster convergence (2,996 iterations, 1h39min). GA tends to preserve coverage, whereas AIS provides superior SINR improvements and faster stabilization.

For azimuth optimization, the reference configuration achieves 87.5% coverage and 23.1% SINR. GA–EM&GIS improves the overall fitness by 10.7% after 2,926 iterations (1h37min), while AIS–EM&GIS yields a 21.1% gain with only 1,831 iterations (1h01min). AIS again demonstrates stronger interference reduction and higher SINR, whereas GA tends to slightly favor coverage.

TABLE II
TILTS AND AZIMUTHS FOR DIFFERENT SITES AND SECTORS ACCORDING TO OPERATOR, AIS–EM&GIS ET GA–EM&GIS

Site	Secteur	Operator		AIS–EM&GIS		GA–EM&GIS	
		Tilts	Azimuts	Tilt Optimization Only	Azimuth Optimization Only	Tilt Optimization Only	Azimuth Optimization Only
Site1	A	5	70	6	120	5	0
	B	5	150	5	250	3	130
	C	6	230	4	320	0	250
Site2	A	0	0	6	170	6	90
	B	4	90	5	240	2	210
	C	4	280	2	340	3	310
Site3	A	6	60	-4	40	-4	50
	B	6	180	6	160	6	160
	C	6	300	4	290	3	320
Site4	A	2	0	-4	0	6	10
	B	2	110	5	60	6	70
	C	2	260	6	120	6	200
Site5	A	4	60	6	100	-3	20
	B	2	180	4	270	5	110
	C	2	300	-1	350	5	290
Site6	A	0	30	2	10	6	0
	B	4	160	5	220	4	130
	C	4	280	3	280	3	240
Site7	A	4	60	6	140	5	80
	B	4	180	6	270	4	200
	C	2	300	4	330	1	340
Site8	A	4	60	3	100	4	20
	B	4	180	6	230	6	120
	C	4	300	6	350	6	240
Site9	A	4	60	1	60	4	20
	B	5	180	6	220	6	200
	C	5	300	-4	330	-4	290
Site10	A	2	40	6	100	0	30
	B	3	180	3	200	2	170
	C	2	280	3	340	3	300
Site11	A	3	110	5	90	6	10
	B	5	240	6	210	6	140
	C	2	350	5	310	3	250
Site12	A	6	60	0	0	0	40
	B	6	180	1	70	0	190
	C	6	300	5	200	5	250
Site13	A	4	0	0	100	1	10
	B	6	130	4	180	2	140
	C	6	260	6	330	-4	270
Site14	A	4	60	6	60	6	140
	B	4	180	6	200	3	220
	C	4	300	2	300	4	310
Site15	A	4	80	6	140	6	130
	B	6	200	0	250	4	260
	C	6	320	6	350	6	330
Site16	A	4	100	-4	70	6	70
	B	4	240	3	200	3	200
	C	2	350	6	320	6	320
Site17	A	0	180	5	90	-2	20
	B	0	330	-3	200	1	80
Site18	A	0	190	0	180	-1	160
	B	0	320	-2	350	1	350
Site19	A	0	50	1	110	2	0
	B	0	160	4	200	6	110
	C	0	320	6	350	5	200

Table II further highlights site- and sector-specific adjustments. Optimized tilts exhibit significant variability, including negative values (e.g., Site 3 Sector A: –4°for both GA and AIS), reflecting strategies to limit interference. Azimuths often deviate from the standard 0°, 120°, 240°distribution, adapting to urban morphology and traffic demand. AIS generally proposes more aggressive adjustments (e.g., Site 16 Sector A: –4°vs. +6°for GA), which explains its higher SINR performance.

Operationally, tilts can be remotely adjusted via *RET*, enabling seamless integration with SON for cost-effective automation. Azimuth adjustments still require mechanical intervention, but the proposed decision-support tool reduces reconfiguration time and operational effort.

Overall, the hybrid GA/AIS–EM&GIS framework delivers substantial improvements over manual configuration. AIS consistently achieves superior SINR performance with faster convergence, while GA maintains slightly higher coverage. This balance makes the approach cost-effective, scalable, and directly applicable to 4G and 5G networks. Moreover, its compatibility with SON and RET mechanisms provides a solid foundation for 5G-Advanced and 6G, where autonomous, multi-parameter optimization will be essential for dense IoT- and URLLC-oriented environments.

The proposed method also exhibits strong scalability and natural adaptability to various network scenarios. Although it has been validated on a medium-sized urban LTE network (Oran), its modular structure—combining EM simulation, GIS data, and metaheuristic algorithms—allows for straightforward transfer to other environments, including suburban, rural, or significantly denser areas. For large-scale networks or forthcoming 5G/6G deployments involving massive MIMO, beamforming, or ultra-dense layouts, a cluster-based approach that partitions the region into locally optimized sub-areas offers an effective solution to reduce computational cost while maintaining adequate accuracy. Furthermore, the integration of AI-based approximation models can enhance this adaptability, ensuring a robust balance between performance, precision, and computational efficiency across diverse operational contexts.

TABLE III
RSRP AND SINR PERFORMANCE ANALYSIS FOR DIFFERENT OPTIMIZATION CONFIGURATIONS AND ALGORITHMS

Optimization Type	**Algorithmic Complexity**	**Algorithm / Config.**	**RSRP (%)**	**SINR (%)**	**Fitness**	**Gain / Operator Config. (%)**	**Convergence [Iterations]**	**Convergence Time**
Manual Optimization Based on Drive Tests	36×13^{57}	Operator's configuration	87.7	24.6	2157.42	0.00	–	–
Tilt Optimization Only	13^{57}	Reference tilt (Tilt = 0°, operator's azimuth)	94.3	12.3	1159.89	-46.24	–	–
		GA–EM&GIS	91.1	28.4	2587.24	19.92	3 374	1h52min
		AIS–EM&GIS	90.7	29.4	**2666.58**	**23.60**	2 996	1h39min
Azimuth Optimization Only	36^{57}	Reference azimuth (operator's tilt, 0°/120°/240°)	87.5	23.1	2021.25	-6.31	–	–
		GA–EM&GIS	87.2	27.4	2389.28	10.75	2 926	1h37min
		AIS–EM&GIS	88.3	29.6	2613.68	21.15	1 831	1h01min

VI. CONCLUSION

This paper proposed a hybrid optimization framework that integrates GA and AIS with an EM propagation model embedded in a GIS environment. The method targeted the separate optimization of antenna tilt and azimuth to improve coverage and service quality in cellular networks. Simulation results showed substantial gains over the operator's baseline configuration: tilt optimization achieved up to +24% improvement with AIS, ensuring faster convergence and stronger interference control, while azimuth optimization provided over +21% gain, enhancing spatial distribution and reducing sector overlap. AIS consistently outperformed GA in terms of link quality, whereas GA slightly favored coverage.

From an operational standpoint, electrical tilt can be remotely adjusted via *RET*, enabling direct integration into *SON* mechanisms without added costs. Although azimuth still requires mechanical intervention, the proposed approach provides decision support that reduces reconfiguration time and expenses. Overall, the framework delivers a cost-effective, scalable, and high-performance solution for 4G and 5G deployments, with strong potential for 5G-Advanced and 6G, especially in ultra-dense networks where continuous parameter adaptation is critical.

Future research will extend this work toward joint tilt–azimuth optimization and explore additional parameters such as transmit power, antenna height, and mechanical tilt. Incorporating advanced AI techniques, including deep learning and reinforcement learning, will further enable predictive and adaptive self-optimization, enhancing QoS in next-generation networks.

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