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PHYSICS-AWARE HYBRID EVOLUTIONARY OPTIMIZATION FRAMEWORK FOR SUPER-DIRECTIVE HMIMO ANTENNA ARRAYS

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Abstract:
Holographic massive multiple-input multiple-output (HMIMO) antenna systems are widely regarded as a foundational technology for sixth-generation (6G) wireless networks due to their ability to provide extreme spatial resolution, near-field beam focusing, and unprecedented spectral efficiency. Achieving these capabilities requires the synthesis of super-directive antenna arrays capable of generating highly focused electromagnetic beams. However, classical super-directive array designs often suffer from severe electromagnetic limitations, including excessive quality factor, narrow bandwidth, poor radiation efficiency, and impedance mismatch, rendering many theoretically optimal solutions practically unrealizable. This paper presents Evo-HMAA, a physics-aware hybrid multi-agent evolutionary optimization framework designed to address these challenges. Evo-HMAA integrates Differential Evolution (DE), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) within a cooperative architecture that enables information sharing among sub-populations. Electromagnetic-aware constraints are embedded directly into a multi-objective fitness formulation that simultaneously optimizes directivity, realized gain, sidelobe level, half-power beamwidth, and impedance matching. In addition, Gaussian Process surrogate modeling is employed to reduce computational complexity during early optimization stages. Extensive simulations conducted in MATLAB, with validation using full-wave electromagnetic simulations in CST Microwave Studio, demonstrate that Evo-HMAA consistently outperforms state-of-the-art standalone and hybrid optimization algorithms. Across array sizes ranging from 2×2 to 20×20 elements, Evo-HMAA achieves up to 118% improvement in directivity, 186% enhancement in realized gain, sidelobe suppression below −59 dB, and impedance matching better than −19 dB. These results confirm Evo-HMAA as a scalable, robust, and electromagnetically realizable optimization framework for next-generation HMIMO antenna systems.

Keywords — **Holographic massive MIMO, super-directive arrays, hybrid evolutionary optimization, electromagnetic-aware optimization, surrogate-assisted optimization**

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I. INTRODUCTION

The rapid evolution of wireless communication systems has driven an ever-increasing demand for higher data rates, ultra-low latency, enhanced reliability, and integrated sensing capabilities. Sixth-generation (6G) wireless networks are expected to extend beyond conventional communication paradigms by incorporating near-field beamforming, holographic radio surfaces, and intelligent electromagnetic environments. Within this context, holographic massive multiple-input multiple-output (HMIMO) antenna arrays have emerged as a key enabling technology, offering unprecedented control over electromagnetic wavefronts through electrically large, ultra-dense planar arrays.

A central requirement for HMIMO systems is the ability to generate highly directive and spatially confined beams, particularly in near-field propagation regimes where traditional far-field beam steering assumptions are no longer valid. Super-directive antenna arrays, characterized by beamwidths significantly narrower than those achievable by uniformly excited arrays of comparable aperture, offer a promising solution to this requirement. By carefully tailoring the excitation amplitudes and phases of individual antenna elements, super-directive arrays can, in principle, achieve extreme spatial selectivity and enhanced interference suppression.

Despite their theoretical appeal, super-directive antenna arrays are notoriously difficult to realize in practice. Decades of electromagnetic research have established that extreme directivity is accompanied by excessive reactive energy storage, leading to high quality factors, narrow operational bandwidths, increased sensitivity to manufacturing tolerances, and severe impedance mismatch. These challenges are further exacerbated in dense HMIMO configurations due to strong mutual coupling among closely spaced elements and increased ohmic and dielectric losses at millimeter-wave and sub-terahertz frequencies.

From a design and optimization perspective, super-directive HMIMO array synthesis constitutes a highly nonlinear, multi-objective, and constrained optimization problem. Performance metrics such as directivity, realized gain, sidelobe level (SLL), half-power beamwidth (HPBW), impedance matching, and radiation efficiency are strongly coupled and often conflicting. Maximizing directivity alone frequently results in solutions with unacceptable efficiency or matching characteristics, highlighting the necessity of physics-aware optimization strategies.

II. THEORETICAL REVIEW

The synthesis and optimization of antenna arrays have long been recognized as challenging problems due to the inherent nonlinearity, multimodality, and conflicting design objectives involved. Traditional analytical techniques, while valuable for gaining physical insight, are often limited to simplified scenarios and struggle to accommodate complex constraints such as mutual coupling, impedance matching, and efficiency. As a result, population-based evolutionary optimization algorithms have become increasingly prominent tools for antenna array design.

Genetic Algorithms (GA) were among the earliest evolutionary techniques applied to antenna array synthesis. Their ability to handle discrete and continuous variables made them suitable for optimizing excitation amplitudes, phases, and element positions. Numerous studies have demonstrated GA-based approaches for sidelobe level reduction, beam shaping, and null steering. However, GA performance is highly sensitive to parameter selection, and the reliance on crossover and mutation operators often leads to slow convergence, particularly in high-dimensional optimization problems such as large-scale HMIMO arrays. Furthermore, GA-based solutions frequently prioritize pattern characteristics without explicitly enforcing electromagnetic realizability constraints.

Differential Evolution (DE) emerged as a powerful alternative due to its strong global search capability and simple control parameters. DE has been successfully employed in array thinning, amplitude-only synthesis, and phase-only optimization. Its mutation and recombination strategies allow efficient exploration of continuous search spaces. Nevertheless, DE tends to require large population sizes and extended computational time when addressing multi-objective problems with strict constraints. In the context of super-directive arrays, DE-optimized solutions may converge toward extreme excitation distributions that result in poor impedance matching and low efficiency if electromagnetic considerations are not incorporated.

Particle Swarm Optimization (PSO) has gained widespread popularity in antenna optimization due to its rapid convergence and intuitive formulation inspired by social behaviour. PSO-based methods have been reported for planar and conformal array synthesis, adaptive beamforming, and pattern nulling. Despite these advantages, PSO is prone to premature convergence and stagnation in multimodal fitness landscapes, particularly when optimizing highly constrained problems such as super-directive HMIMO arrays. The lack of inherent diversity preservation mechanisms often limits its effectiveness for large-scale optimization.

To overcome the limitations of single-metaheuristic approaches, hybrid optimization strategies have been proposed. GA–PSO and DE–PSO hybrids aim to combine the exploration strength of evolutionary algorithms with the fast convergence of swarm intelligence. Several studies have reported improved performance using hybrid approaches for antenna array pattern synthesis. However, most existing hybrids operate sequentially rather than cooperatively, and they rarely address electromagnetic realizability explicitly. Moreover, scalability to ultra-dense HMIMO configurations remains largely unexplored.

In parallel, surrogate-assisted evolutionary optimization has emerged as a promising approach to reduce the computational burden associated with electromagnetic simulations. Techniques based on Gaussian Processes, neural networks, and polynomial regression have been used to approximate fitness functions and guide the search process. While surrogate models can significantly accelerate convergence, their integration into antenna optimization frameworks requires careful management to avoid loss of accuracy, particularly in highly nonlinear regions of the design space.

Despite the substantial body of work on evolutionary antenna optimization, several critical gaps remain. First, most studies focus on far-field array synthesis and do not address the unique challenges of near-field HMIMO systems. Second, electromagnetic realizability constraints such as impedance matching and efficiency are often treated as secondary considerations or omitted entirely. Third, cooperative hybrid frameworks that explicitly leverage complementary metaheuristics in parallel remain underdeveloped. This paper addresses these gaps by proposing a cooperative, physics-aware hybrid evolutionary optimization framework specifically tailored for super-directive HMIMO arrays

III. METHODOLOGY

This section presents the proposed Evo-HMAA framework in detail, including the cooperative hybrid architecture, mathematical formulation of the optimization problem, electromagnetic-aware constraint handling, surrogate-assisted evaluation mechanism, and algorithmic workflow. The core design principle of Evo-HMAA is that super-directive HMIMO array synthesis is a highly nonlinear, multi-objective, and electromagnetically constrained problem that cannot be effectively solved by a single metaheuristic.

Evo-HMAA adopts a cooperative multi-agent evolutionary architecture composed of three parallel sub-populations implementing Differential Evolution (DE), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), respectively. Each sub-population evolves independently using its native operators, while information exchange is enabled through an elite migration mechanism. This architecture allows Evo-HMAA to leverage the complementary strengths of the constituent algorithms: DE provides strong global exploration capability, GA enhances genetic diversity through recombination, and PSO ensures rapid convergence via social learning.

Unlike sequential hybrid methods, Evo-HMAA operates all sub-populations simultaneously. At predefined migration intervals, elite solutions from each sub-population are exchanged and injected into the others, replacing low-performing individuals. This cooperative strategy mitigates premature convergence, preserves diversity, and

accelerates convergence toward high-quality solutions. Figure 1 illustrates the overall Evo-HMAA architecture and information exchange process, including the parallel DE, GA, and PSO sub-populations and the elite migration mechanism.

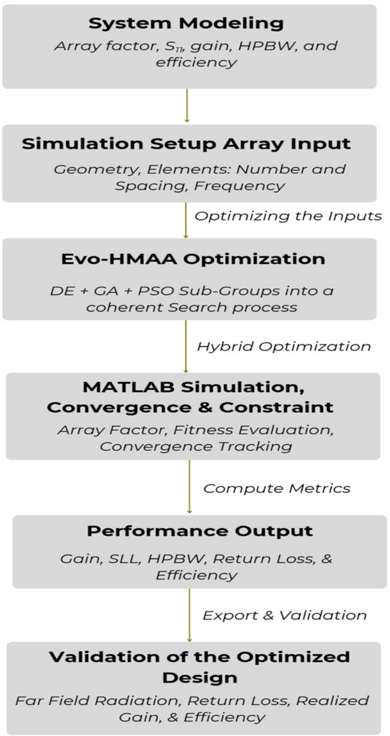

Fig. 1 Methodological Framework for Evo-HMAA-Based Optimization of Planar Arrays

The super-directive HMIMO array synthesis problem is formulated as a constrained multi-objective optimization problem. Consider a planar HMIMO array consisting of MxN radiating elements, each characterized by a complex excitation coefficient

$$a_n = A_n e^{j\phi_n}, \quad n = 1, 2, \ldots, N$$

The objective is to determine XX such that array directivity and realized gain are maximized while sidelobe level, beamwidth, impedance mismatch, and efficiency degradation are minimized. These objectives are inherently conflicting, particularly under super-directive conditions.

To ensure physical realizability, Evo-HMAA employs an electromagnetic-aware composite fitness function. The fitness formulation balances radiation performance against impedance matching and efficiency constraints. Designs that achieve high directivity at the expense of extreme reactive energy storage or poor matching are penalized. Adaptive penalty functions dynamically adjust penalty severity based on constraint violation magnitude, allowing early exploration and gradual convergence toward feasible solutions.

Hard constraints are imposed on excitation amplitudes and phases to ensure hardware feasibility. In addition, reflection coefficient thresholds and minimum radiation efficiency requirements are enforced to eliminate unrealizable super-directive solutions. The combination of hard constraints and adaptive penalties provides robust constraint handling without excessively restricting the search space.

To reduce computational cost, Evo-HMAA integrates Gaussian Process surrogate modeling during early optimization stages. The surrogate model approximates the fitness landscape using a limited number of high-fidelity electromagnetic evaluations. Surrogate predictions are selectively validated and corrected, ensuring convergence accuracy while significantly reducing simulation time.

The Evo-HMAA workflow consists of population initialization, electromagnetic-aware fitness evaluation, surrogate model training, cooperative evolution, elite migration, and convergence assessment. This structured workflow enables efficient navigation of the complex optimization landscape associated with super-directive HMIMO arrays.

Table I summarizes the key algorithm parameters used for the DE, GA, and PSO sub-populations, including population size, mutation factors, crossover rates, inertia weights, and migration intervals. These parameters were selected based on extensive preliminary studies reported in the thesis to ensure fair benchmarking and stable convergence.

TABLE I
KEY ALGORITHMIC PARAMETERS FOR THE EVO-HMAA FRAMEWORK, INCLUDING DE, GA, AND PSO SUB-POPULATION SETTINGS

Parameter	Value / Description
Frequency Band	26.5–29.5 GHz (Cantered at 28 GHz)
Wavelength Reference (λ)	10.7 mm
Array Sizes	2×2 to 20×20 (step size: 2×2)
Element Count Range	4 to 400
Evo-HMAA Subgroups	DE (147), GA (147), PSO (147) – Total: 441
Generations	250
Inter-element Spacing Bounds	0.25λ to 0.75λ
Excitation Normalization	Unit power across all elements
CST Solver Type	Frequency-domain full-wave EM
CST Substrate	RT/Duroid 5880 (ε = 2.2, h = 0.787 mm)
CST Element Type	Edge-fed rectangular patch (discrete port per element)
Validation Metrics	Realized Gain, S11, HPBW, Directivity, SLL
MATLAB Version	R2023b (64-bit), Custom Optimization Toolbox
CST Version	CST Studio Suite 2024

Full-wave electromagnetic simulations were conducted using CST Microwave Studio to validate MATLAB-based optimization results. Benchmark comparisons were performed against standalone GA, DE, PSO, and conventional hybrid algorithms using identical simulation settings.

TABLE 2
CST VS MATLAB OUTPUTS

Array Size (M×N)	MATLAB Gain (dBi)	CST Gain (dBi)	ΔG (dB)
2×2	10.14	10.14	0
4×4	16.154	16.154	0
6×6	19.672	19.656	0.016
8×8	22.114	22.089	0.025
10×10	23.81	23.905	–0.095
12×12	25.22	24.315	0.905
14×14	26.32	24.78	1.54
16×16	27.4	25.345	2.055
18×18	28.29	25.287	3.003
20×20	29.05	25.053	3.997

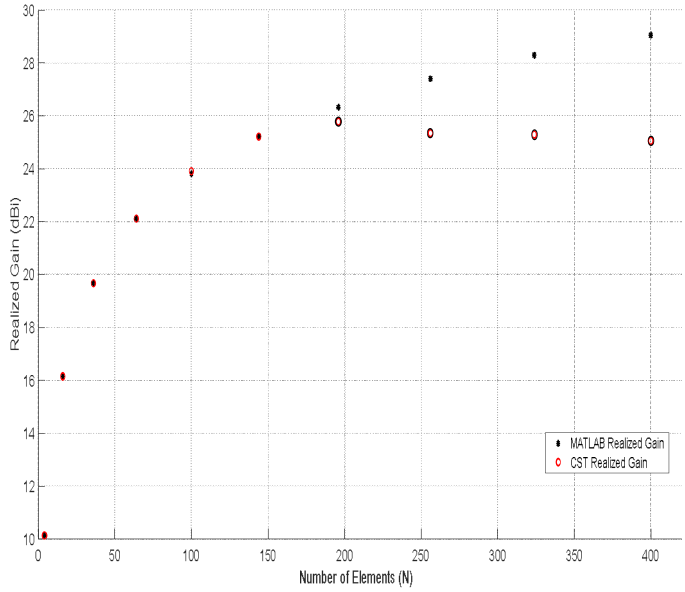

Fig. 2 CST vs MATLAB Realized Gain Validation Across Array Sizes.

IV. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed Evo-HMAA framework through extensive simulation studies and comparative benchmarking. Results are analyzed in terms of convergence behavior, radiation performance, electromagnetic realizability, scalability, robustness, and computational efficiency.

Figure 3 compares the convergence behavior of Evo-HMAA with standalone GA, DE, PSO, and conventional hybrid algorithms for a representative 10×10 HMIMO array. Evo-HMAA exhibits rapid initial convergence driven by PSO exploitation, followed by sustained improvement enabled by DE exploration and GA diversity preservation. Benchmark algorithms either stagnate or converge prematurely, confirming the advantage of the cooperative hybrid architecture.

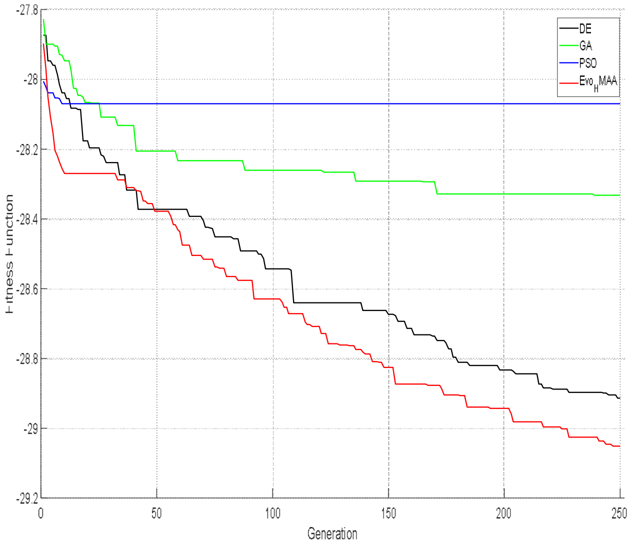

Fig. 3 Convergence comparison of Evo-HMAA against standalone GA, DE, and PSO

As summarized in Table III, Evo-HMAA achieves up to 118% improvement in directivity and 186% enhancement in realized gain relative to uniform excitation. Sidelobe levels are consistently suppressed below −59 dB, significantly outperforming benchmark methods. These results confirm the effectiveness of physics-aware optimization.

TABLE 3
RADIATION PERFORMANCE METRICS OF EVO-HMAA-OPTIMIZED HMIMO ARRAYS ACROSS SIZES FROM 2×2 TO 20×20

Array Size (M×N)	Element Size	Realized Gain (dBi)	Return Loss (S_{11}, dB)	HPBW (°)	Directivity (dBi)	SLL (dB)
2×2	4	10.14	-18.79	59.80	16.03	-310.96
4×4	16	16.15	-18.63	26.20	22.04	-310.96
6×6	36	19.67	-17.95	17.00	25.56	-86.78
8×8	64	22.11	-20.42	12.60	28.00	-51.09
10×10	100	23.81	-18.41	10.00	29.70	-56.12
12×12	144	25.22	-18.20	8.40	31.12	-54.24
14×14	196	26.32	-21.32	7.20	32.21	-50.35
16×16	256	27.40	-19.40	6.20	33.29	-51.11
18×18	324	28.29	-19.54	5.60	34.18	-56.04
20×20	400	29.05	-19.03	5.00	34.94	-58.94

Figure 4 presents the reflection coefficient (S_{11}) characteristics of the optimized arrays. Unlike many super-directive approaches, Evo-HMAA explicitly enforces impedance constraints. Optimized designs achieve reflection coefficients better than −19 dB while maintaining acceptable radiation efficiency.

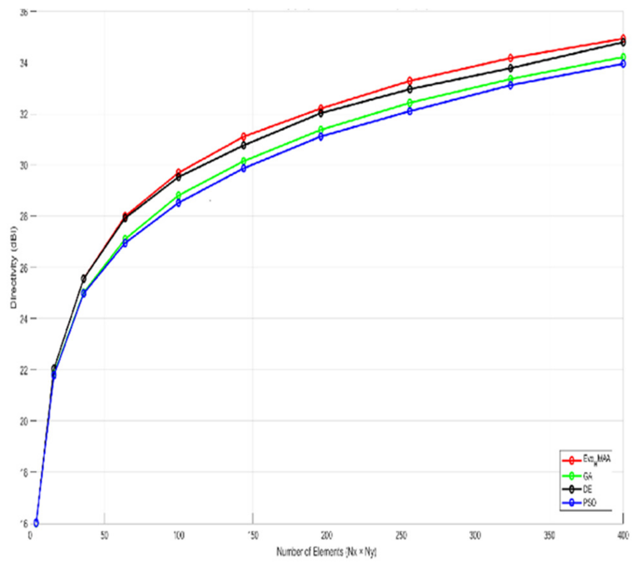

Fig. 4 Impedance Matching (S_{11} Characteristics)

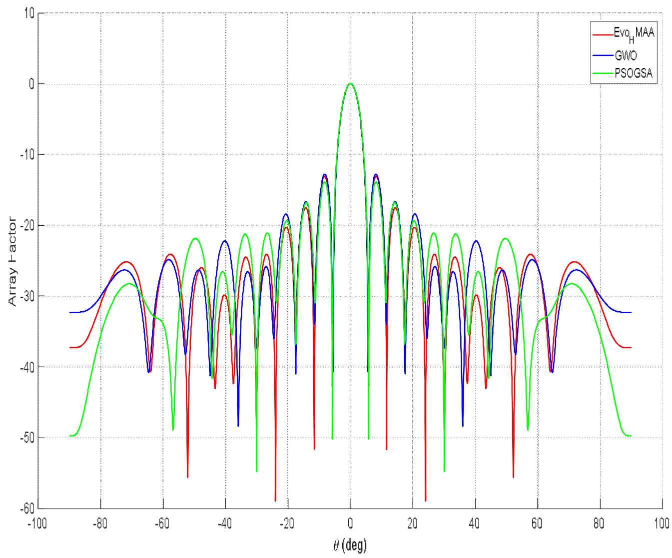

Fig. 5 Radiation and beam pattern comparison demonstrating sidelobe suppression and main-lobe sharpening

Figure 6 illustrates the scalability of Evo-HMAA for array sizes ranging from 2×2 to 20×20 elements. Performance gains scale consistently with array size, with no evidence of convergence instability. This scalability is attributed to the cooperative multi-agent architecture and surrogate-assisted evaluation strategy.

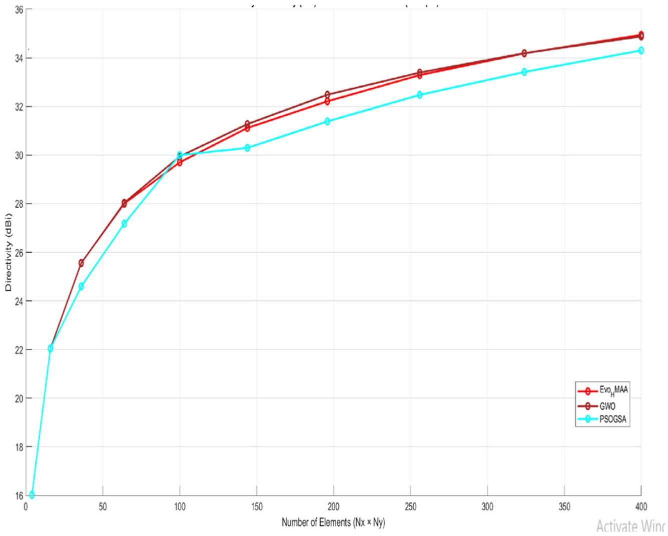

Fig. 6 Scalability Analysis (Directivity vs Array Size).

Robustness analysis was conducted by introducing random perturbations in excitation amplitudes and phases. Evo-HMAA-optimized arrays exhibit reduced sensitivity to perturbations compared to benchmark designs, indicating improved tolerance to fabrication and implementation errors.

Although Evo-HMAA employs multiple parallel sub-populations, surrogate modeling significantly reduces the number of high-fidelity electromagnetic evaluations. Overall computational cost remains comparable to, or lower than, standalone algorithms for equivalent performance levels.

V. CONCLUSIONS

This paper presented Evo-HMAA, a physics-aware hybrid evolutionary optimization framework for the synthesis of super-directive holographic massive MIMO (HMIMO) antenna arrays. By integrating Differential Evolution, Genetic Algorithm, and Particle Swarm Optimization within a cooperative multi-agent architecture, Evo-HMAA effectively balances global exploration, diversity preservation, and rapid convergence. Unlike conventional evolutionary approaches, electromagnetic realizability constraints were embedded directly into the optimization process, ensuring that improvements in directivity and spatial selectivity were not achieved at the expense of impedance matching or radiation efficiency.

Comprehensive simulation studies, validated using full-wave electromagnetic analysis, demonstrated that Evo-HMAA consistently outperforms standalone and conventional hybrid optimization algorithms across a wide range of array sizes. Significant improvements in directivity, realized gain, sidelobe suppression, and impedance matching were achieved while maintaining scalability and robustness. The incorporation of surrogate-assisted evaluation further reduced computational cost, enabling efficient optimization of large-scale HMIMO configurations relevant to emerging 6G systems.

The results confirm that physics-aware cooperative hybrid optimization provides a viable pathway toward electromagnetically realizable super-directive HMIMO arrays. Future work will focus on experimental validation using fabricated array prototypes, extension to broadband and reconfigurable holographic surfaces, and integration with joint communication-and-sensing system architectures.

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