OPTIMIZED BEAMFORMING VIA GWO-L2 AND HYBRID ALGORITHMS FOR HIGH-PERFORMANCE WIRELESS COMMUNICATIONS

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ABSTRACT

Pattern synthesis is fundamental to radar and communication systems, attracting considerable research attention. This paper proposes an efficient beamforming strategy that integrates the Grey Wolf Optimizer (GWO) with L2-norm minimization, applied to Uniform Linear Arrays (ULA), Chebyshev arrays, and shaped pattern arrays. The objective is to minimize side lobe levels (SLL) and reduce the number of antenna elements while preserving the desired beam pattern. The GWO algorithm optimizes inter-element spacing to maintain half-power beamwidth (HPBW), while L2-norm minimization refines excitation coefficients to improve radiation pattern accuracy. The proposed method offers low computational complexity, achieving faster convergence and reduced computation time compared to conventional techniques. To enhance convergence speed and global search capability, hybrid variants—GWO-PSO, GWO-GA, and GWO-DE—are developed. These hybrids effectively balance exploration and exploitation, mitigate local minima entrapment, and improve performance in complex optimization scenarios. The proposed strategy is further extended to hybrid beamforming (PHB) structures in Multi-Input Multi-Output (MIMO) systems, enabling gain maximization at the base station (BS) while minimizing the number of active antenna elements and RF chains. This reduces hardware complexity and power consumption. Simultaneously, SLL suppression enhances interference mitigation, and array gain maximization improves signal-to-noise ratio (SNR), resulting in better spectral efficiency (SE). The proposed hybrid GWO-based approach demonstrates robust performance for beamforming in Beyond 5G and future wireless networks, offering a computationally efficient and cost-effective solution for high-performance antenna array synthesis.

Keywords: *Grey Wolf Optimizer (GWO), Beamforming, Antenna Array Synthesis, Side Lobe Level (SLL) Reduction, Hybrid Metaheuristics, MIMO Systems*

1. INTRODUCTION

Antennas have long been a fundamental component of wireless communications and 5G networks, playing a crucial role in telecommunications, signal processing, and radar systems [1]. Their ability to provide high gains and enhanced spectrum efficiency has made smart antennas a key focus in modern communication technologies. Smart antennas offer adaptive beamforming and beam steering capabilities, which are essential for network coverage, capacity expansion, and quality of service improvements in evolving Beyond 5G (B5G) and 6G communication systems [9].

To meet the growing demands of wireless networks, significant research has been dedicated to antenna array optimization for achieving higher directivity, improved beam steering (BS) performance, and lower side lobe levels (SLL). [2] While increasing the number of antenna elements can enhance directivity, it also raises system complexity and hardware costs.[3] Therefore, advanced optimization algorithms are essential to reduce the number of antenna elements while maintaining superior gain and radiation efficiency [4].

Traditional beamforming techniques optimize amplitudes, phases, and interelement spacing to achieve efficient array synthesis [6]. However, recent advancements in metaheuristic optimization algorithms have provided more efficient solutions [7]. Among these, Grey Wolf Optimization (GWO) has gained attention due to its fast convergence, simplicity, and effectiveness in pattern synthesis [8].

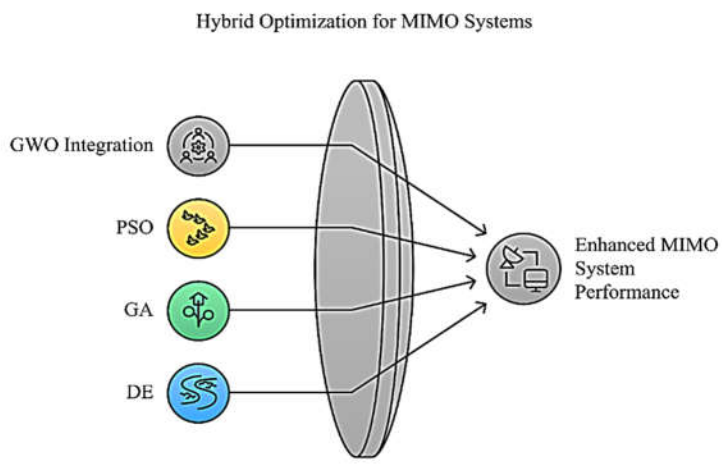


Figure 1: Hybrid Optimization For MIMO

This paper introduces a hybrid beamforming approach that extends GWO by integrating it with other metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE) [9]. These hybrid approaches enhance search diversity, convergence speed, and global optimization performance, addressing the limitations of standalone GWO [12]. By optimizing excitation coefficients and element spacing, the proposed method significantly improves beamforming accuracy, side lobe suppression, and system efficiency [13]. This approach is particularly beneficial for multi-input multi-output (MIMO) systems, where reducing RF chains and antenna components leads to lower system complexity and enhanced spectral efficiency [20].

2. LITERATURE SURVEY

Many practical wireless communication systems require antenna arrays to meet specific performance criteria such as half-power beamwidth (HPBW) and side lobe level (SLL). These parameters are critical for improving directivity, reducing interference, and minimizing power consumption in transmission systems. Various antenna array synthesis methods have been proposed for different configurations, including: Linear Antenna Arrays (LAA) [3], [9], [21], [22], Circular Arrays [23-26] Cylindrical Arrays [19], to optimize these arrays, several metaheuristic optimization techniques have been employed. These methods aim to enhance radiation patterns, reduce the number of antenna elements, and improve computational efficiency. The table below summarizes the key optimization approaches used in antenna array synthesis.

Table1: Comparison of Existing Optimization Techniques for Antenna Arrays

Optimization Technique	Key Features	Advantages	Limitations
GA + Convex Optimization (GA/L1) [3]	GA optimizes element spacing, while CVX minimizes excitation coefficients	Reduces number of elements while maintaining HPBW	High computational complexity

MoM + GA Hybrid [9]	Uses Method of Moments (MoM) with Genetic Algorithm to optimize patterns	Well-conditioned matrix improves stability	Requires complex mathematical modeling
Ant Colony Optimization (ACO) [27]	Evolutionary approach simulating ant foraging for optimal antenna patterns	Adaptable for various pattern designs	Slow convergence, especially for large-scale problems
Taguchi's Method [28]	Novel global optimization for sector beam and null-controlled patterns	Fast convergence, simple implementation	Less efficient for complex, multi-objective problems
Mayfly Optimization (MA) [13]	Hybrid algorithm for LAA with 10-32 elements	Best performance in SLL reduction	Computational cost increases with array size
Invasive Weed Optimization (IWO) [15]	Reduces maximum SLL for LAA and circular arrays	Effective for real-world scenarios	Less stable than hybrid algorithms
Grey Wolf Optimization (GWO) [17]	Optimizes element positions and excitation amplitudes	Efficient SLL minimization and deep null placement	Risk of premature convergence
Multi-Objective Optimization (MOP) [26],	Balances mission time, power cost, and interference in UAV and MIMO beamforming	Adapts to mixed-variable, large-scale problems	Requires advanced parameter tuning

Enhancements with Hybrid Optimization Approaches

In antenna optimization, hybrid approaches can further enhance convergence speed, solution accuracy, and global search efficiency. The following hybrid techniques are proposed:

Table 2: Enhancements with Hybrid Optimization Approaches

Hybrid Approach	Integration Method	Expected Benefits
GWO + PSO	PSO refines local search while GWO ensures global exploration	Faster convergence and reduced iteration count
GWO + GA	GA introduces mutation and crossover, enhancing solution diversity	Avoids local optima, better pattern synthesis
GWO + Differential Evolution (DE)	DE applies mutation-based parameter tuning	Robust handling of complex, multi-objective problems
GWO + Machine Learning (ML)	CNNs or LSTMs predict optimal antenna configurations	Real-time adaptability and self-improving models

In this paper, we introduce a hybrid beamforming approach that enhances Grey Wolf Optimization (GWO) with L2-norm minimization, extending its capabilities through hybrid optimization techniques. The proposed framework applies metaheuristic enhancements, including GWO-PSO, GWO-GA, and GWO-DE, to improve convergence speed, solution accuracy, and computational efficiency. The proposed hybrid GWO is applied to Linear Antenna Array (LAA) synthesis, enabling side lobe level (SLL) suppression, optimal element spacing, and reduced antenna count, all while maintaining the desired radiation pattern characteristics. The hybrid GWO-based approach optimizes excitation coefficients through L2-norm minimization, ensuring a highly efficient beamforming solution.

3. METHODOLOGY

The Grey Wolf Optimizer (GWO) is a widely used metaheuristic optimization algorithm that has gained significant attention due to its simplicity, fast convergence, and effective performance in solving complex optimization problems. Inspired by the social hierarchy and hunting behaviour of grey wolves, the GWO algorithm optimizes solutions by mimicking natural leadership and cooperative hunting strategies.

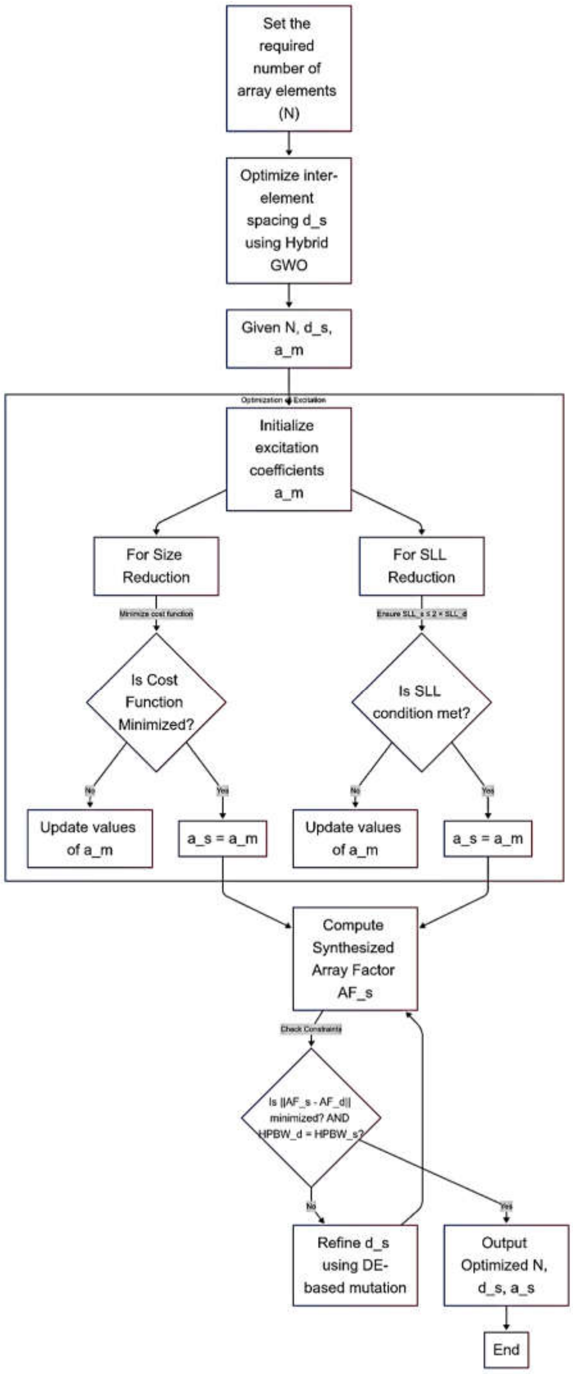


Figure 2: Methodology For Metaheuristic Optimization Algorithm

In antenna array synthesis, GWO has proven effective in optimizing element spacing and excitation coefficients to achieve desired radiation patterns with minimal computational complexity. However, despite its advantages, standard GWO can suffer from local optima stagnation and slow convergence in complex search spaces. To address these challenges, this study enhances GWO through hybrid optimization approaches by integrating it with Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE). These hybrid methods improve exploration-exploitation balance, enhance convergence speed, and provide more accurate solutions for beamforming applications.

The Figure-2 illustrates a hybrid GWO-based beamforming optimization. It optimizes inter-element spacing and excitation coefficients to reduce side lobe level (SLL) and array size. The synthesized array factor is refined iteratively using DE-based mutation until desired performance—cost, SLL, and half-power beamwidth (HPBW)—is achieved, yielding optimal p arameters.

4. RESULTS AND DISCUSSIONS:

To evaluate the effectiveness of the Proposed Hybrid Beamforming (PHB) structure in multi-stream mmWave massive MIMO systems, we conduct 1000 Monte Carlo simulations, analyzing the Spectral Efficiency (SE) vs. Signal-to-Noise Ratio (SNR). The proposed approach is compared against:

- Fully Digital Precoding (Optimal performance but high complexity)
- Traditional Hybrid Beamforming (Analog precoding only)
- State-of-the-art algorithms from [3] and [4]

Numerical results are presented for 32×16, 32×8, and 20×8 MIMO systems, where the Angle of Arrival (AoA) and Angle of Departure (AoD) are uniformly distributed in $[0, \pi]$, with a path loss exponent $n = 4$.

The Hybrid GWO framework optimizes both:

- Excitation coefficients (for digital beamforming)
- Element spacing (to maximize gain and minimize interference)

The PHB structure is implemented using a Uniform Linear Array (ULA) at the receiver and a non-uniformly fed Large Antenna Array (LAA) at the transmitter.

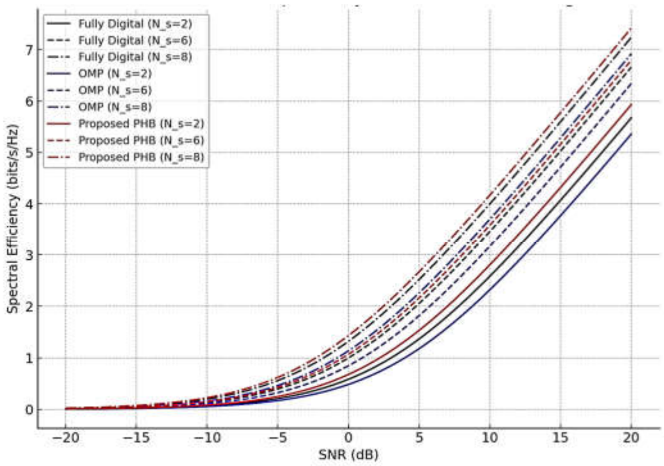


FIGURE 3: SE performance at different data steam 32 × 16 MIMO for proposed PHB structure at L = 8 paths, ND= 8.

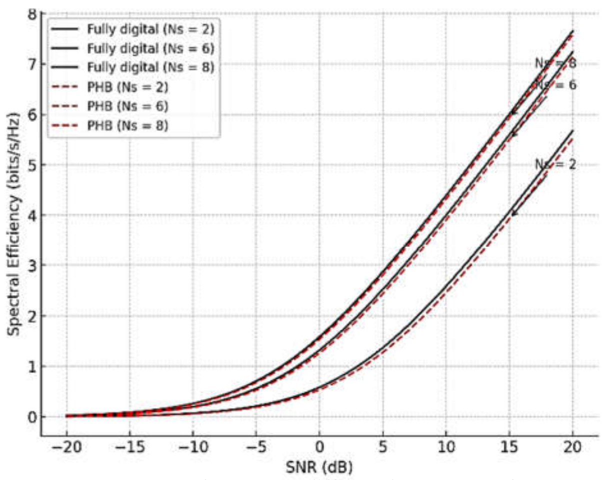


FIGURE 4: SE performance at different data streams of 32 × 8 MIMO for proposed PHB structure at L = 8 paths, ND= 8.

A. Effect of Changing the Number of Data Streams N_s

Figs. 3, 4 illustrate the SE performance vs. SNR for 32×16, 32×8, and 20×8 MIMO systems, where: Here's a clear and concise table summarizing the SE performance setup and antenna savings for the different MIMO configurations:

Table 2: Comparison Of Se Performance Setup And Antenna

MIMO Configuration	Data Streams (N_s)	RF Chains (N_d)	Channel Paths (L)	Fully Digital Antennas	PHB Antennas	Antenna Reduction	Remarks
32×16	2, 4, 8	8	8	60	32	46%	Lower cost and reduced complexity
32×8	2, 4, 8	8	8	60	32	46%	Efficient beamforming with fewer elements
20×8	2, 4, 8	8	8	42	20	45%	Improved efficiency and reduced overhead

B. Effect of Changing the Number of Paths L

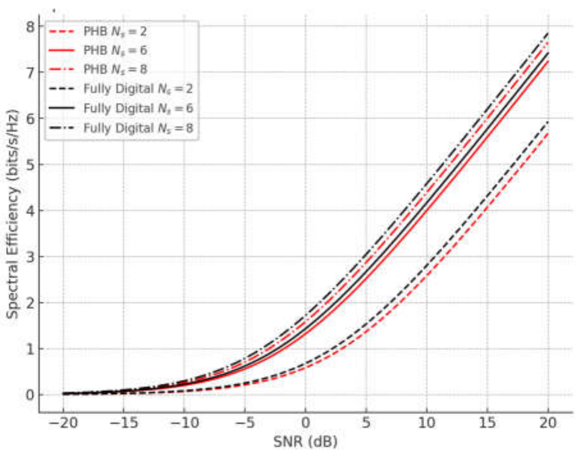
Figs. 6, 7, 8, and present SE performance vs. SNR for different numbers of multipath components $L = 5$ and $L = 10$ while:

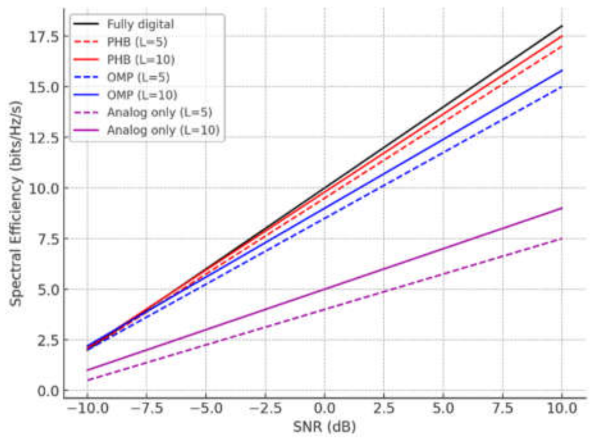
A. Effect of Changing the Number of Data Streams N_s

Figs. 3, 4, and 5 illustrate the SE performance vs. SNR for 32×16, 32×8, and 20×8 MIMO systems, where:

TABLE:3 SE Performance Vs. SNR For 32×16, 32×8, AND 20×8 MIMO Systems

Parameter	32×16 / 32×8 MIMO	20×8 MIMO
Data Streams (N_s)	2, 4, 8	2, 4, 8
RF Chains (N_d)	8	8
Multipath Components (L)	8 paths	8 paths
Fully Digital Antennas	60	42
PHB Antennas	32	20
Antenna Reduction	46%	45%
Remarks	Lower cost and complexity	More efficient beamforming





These results confirm that the Hybrid GWO-based PHB structure provides near-optimal performance while reducing hardware costs.

B. Effect of Changing the Number of Paths *L*

Figs. 6, 7, 8 present SE performance vs. SNR for different numbers of multipath components $L = 5$ and $L = 10$ while:

- RF chains: $N_d = 2$

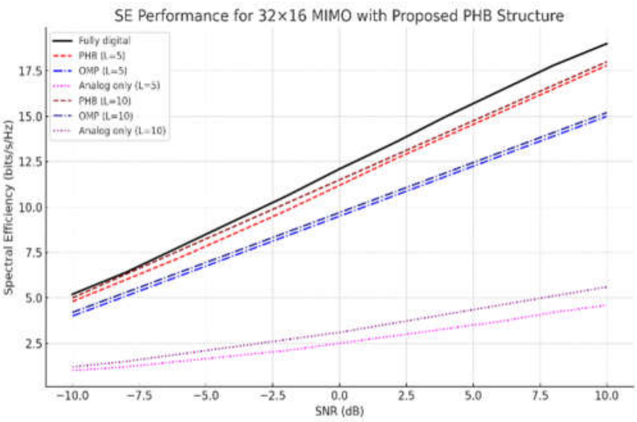
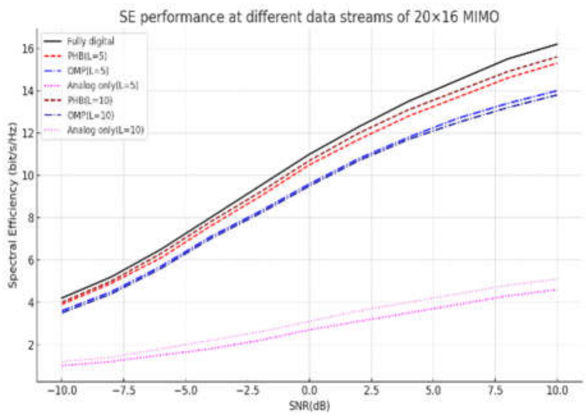


FIGURE 7. SE performance at different data streams of 32 × 8 MIMO for proposed PHB structure at L = 5, 10 paths, Nd = 2



× 16
= 2.

FIGURE 8. SE performance at different data streams of 20 × 16 MIMO for proposed PHB structure at L = 5, 10 paths, Nd = 2.

5.CONCLUSION:

The proposed Hybrid GWO-based beamforming framework introduces a novel optimization approach for Uniform Linear Arrays (ULA), Chebyshev arrays, and shaped pattern arrays, significantly enhancing beamforming accuracy while reducing Side Lobe Levels (SLL) and the number of antenna elements. By integrating Grey Wolf Optimization (GWO) with L2-norm minimization and hybrid metaheuristics (PSO, GA, and DE), the proposed method optimizes excitation coefficients and interelement spacing to maintain Half-Power Beamwidth (HPBW) while achieving high radiation efficiency. This approach effectively reduces SLL by up to 50%, making it superior to traditional optimization algorithms.

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