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Research Article

Evaluation of Beamforming Optimization Techniques on Multibeam Antenna for 5G wireless Communications

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ABSTRACT

With the rapid evolution of 5G wireless communications, the demand for efficient and reliable Multibeam Antenna (MBA) systems has increased significantly. Beamforming optimization techniques play a crucial role in maximizing the performance of these antenna systems. This paper presents an evaluation of three popular optimization algorithms, Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Spider Monkey Optimization (SMO), applied to beamforming optimization in an MBA for 5G wireless communications. The evaluation of these techniques is conducted based on several performance metrics, including scanning performance, scanning loss, gain, and radiation pattern. Each optimization algorithm is applied to the MBA system, and the resulting beamforming configurations are analyzed and compared. The experimental results indicate that while PSO and ABC demonstrate promising performance, SMO consistently outperforms the other two algorithms. SMO achieves higher scanning performance, lower scanning loss, improved gain, and more accurate radiation patterns compared to PSO and ABC. The superiority of SMO can be attributed to its unique optimization approach, which efficiently searches for optimal beamforming solutions in a high-dimensional space. The findings of this study provide valuable insights into the effectiveness of different optimization techniques for beamforming in MBA systems for 5G wireless communications. The results contribute to enhancing the performance and reliability of 5G wireless communications networks by enabling efficient MBA design and deployment.

Keywords: *5G Communications, Antenna, Optimization, Radiation Pattern, Scanning Performance, Transmitter, Receiver*

INTRODUCTION

Multibeam Antenna (MBA) technologies are a critical component of 5G wireless communications, offering numerous advantages and capabilities to support the high-speed, low-latency, and ubiquitous connectivity requirements of the fifth-generation network [1]. Here are some key reasons why MBAs are important for 5G:

- Increased Capacity and Spectral Efficiency: MBA enables simultaneous transmission and reception of multiple beams, allowing for spatial multiplexing [2]. This means that multiple users or devices can be served concurrently in different beams, significantly increasing the network's capacity and spectral efficiency. By dividing the available spectrum into multiple beams, MBA maximizes the utilization of frequency resources and supports higher data rates.
- Enhanced Coverage and Connectivity: MBA provides improved coverage and connectivity in 5G networks [3]. By directing focused beams towards specific areas or users, they can enhance signal strength and extend coverage, particularly in challenging environments such as dense urban areas or remote rural regions. This capability helps bridge the digital divide and ensures a seamless user experience across various deployment scenarios.
- Beamforming and Massive MIMO: MBA technologies are often integrated with beamforming and massive Multiple-Input Multiple-Output (MIMO) techniques. Beamforming involves dynamically steering beams toward specific users or devices, improving signal quality, and mitigating interference [4]. Massive MIMO, which utilizes a large number of antennas, can be efficiently implemented with MBA to enhance spatial resolution, increase system capacity, and enable advanced signal processing algorithms.

- Flexibility and Dynamic Adaptation: MBA offers flexibility and adaptability to meet the dynamic requirements of 5G networks. By dynamically adjusting beam directions, widths, and power allocations, MBA can adapt to changing user demands, traffic patterns, and interference environments. This adaptability ensures efficient utilization of network resources, enhances network performance and enables seamless handovers in mobility scenarios.
- Efficient Spectrum Utilization: Spectrum is a valuable and limited resource in wireless communications [5]. MBA technologies optimize spectrum utilization by allowing for frequency reuse through spatial separation. By directing beams in different directions and exploiting spatial diversity, MBA enables efficient spectrum utilization within a cell or network, increasing spectral efficiency and accommodating a higher number of users.
- Support for Millimeter-wave (mm-Wave) Frequencies: mm-Wave frequencies are a key component of 5G networks, offering vast bandwidth for ultra-fast data rates [6]. However, mmWave signals have limited propagation characteristics and are susceptible to path loss and blockages. MBA plays a crucial role in addressing these challenges by focusing beams and directing signals toward users, overcoming propagation losses, and improving coverage and reliability in mmWave deployments.

In summary, MBA technologies are essential for the successful implementation of 5G wireless communications. They enable increased capacity, enhanced coverage, improved connectivity, efficient spectrum utilization, and support for advanced techniques such as beamforming and massive MIMO. By harnessing the capabilities of MBA technologies, 5G networks can deliver high-performance, reliable, and scalable wireless connectivity for a wide range of applications and use cases. One of the main drawbacks of 5G communication is the issue of signal propagation at higher frequencies, specifically in the mm-Wave spectrum. These frequencies offer high bandwidth and data rates but suffer from limited coverage and susceptibility to blockages and path loss. Beamforming optimization plays a crucial role in overcoming these challenges and improving the performance of 5G communication networks. By leveraging beamforming optimization techniques, 5G networks can deliver higher performance, extended coverage, and reliable connectivity, ensuring the successful deployment and operation of 5G communication systems.

LITERATURE

The work [7] covers a wide range of topics related to MBA, including passive MBA using beamforming circuits and quasi-optical components, multi-beam phased-array antennas made possible by different phase-shifting methods, and digital MBAs with different system topologies. Their workings, designs, and implementations are examined, as well as various examples that demonstrate their utility. The limitations of these MBAs, as well as the challenges of deploying them in future 5G massive MIMO wireless systems, are also investigated. The performance of MBA systems is forecasted in the study [8], where scan loss and half-power beam width are used as performance metrics. The validation of these systems is conducted by employing functional transmit arrays operating in the Ka and V frequency bands. The study introduces an antenna concept that demonstrates the potential of reducing the effects of human blockage on mm-Wave frequencies by combining multiple beams. To evaluate the communication performance, the block error rate is measured using a simulation tool that incorporates the 5G physical communication chain. In the study [9], the focus is on integrated applications of 4G and mm-wave 5G, as well as future applications for IoT devices. The concept of a dual-band antenna with a wide frequency range is introduced, featuring a tapered slot that serves as both a low-frequency resonant open-ended slot and a high-frequency high-gain Vivaldi antenna. By altering the slot's geometry or incorporating multiple sections, the impedance bandwidth is improved. Through this approach, a multiband antenna is developed, operating in the range of 2.5 to 6 GHz, with an mm-wave frequency gain of 10 dBi. The study extensively evaluates various parameters such as return loss, radiation efficiency, gain, total scan pattern, and coverage efficiency, both analytically and experimentally, demonstrating the effectiveness and validity of the antenna design.

In paper [10], a beamforming metasurface is introduced as a solution to reduce the time needed for the initial access (IA) procedure compared to conventional systems utilizing phased array antennas (PAAs). The key advantage of this metasurface is its ability to simultaneously transmit multiple messages in different directions. Numerical data supports the claim that the IA time can be significantly reduced while maintaining a comparable success rate. This system exhibits promising characteristics for the evolving radio and smart electromagnetic environment, offering benefits such as parallel computation, high gain, and scalability for larger systems. The study

[11] investigates lens antenna miniaturization, planarization, and simple integration while retaining the lens antenna's high-quality focusing performance and wide-angle scanning capabilities. This thesis's main contribution is a new type of multi-beam lens antenna that is both small and made entirely of metal. The lens is an air-filled lens antenna developed on the geodesic Luneburg lens antenna theory, featuring a flatter lens profile and a simpler lens curve. The lens antenna has a 15.4 dB gain and ±70° beam width in the H-plane, according to simulations. The research [12] introduces a fresh method for building antenna arrays with different beam patterns, which will be used in 5G and upcoming wireless massive MIMO communication networks. For maximum concentration of radio energy in user-designated coverage zones, the approach optimises the excitation phases and amplitudes of each array element. In order to optimise the number of beams, their forms, orientations, power levels, and the desired sidelobe patterns, the suggested method makes use of genetic algorithms and PSO. Simulation results demonstrate that this method generates optimal beam patterns that can be used to distribute radiation energy efficiently in mobile communication base stations. Paper [13] introduces a theoretical framework for generating individually programmable multiple beams using the generalized joined coupler (GJC) matrix, which includes the Blass matrix and its derivatives. By adjusting the phase shifters in the corresponding rows of the GJC matrix, the direction of each beam can be altered. The study presents a matrix theory and proposes an optimization approach using particle swarm optimization to synthesize such matrices and achieve control over beam orientations and sidelobes. Numerical results highlight the effectiveness of the particle swarm optimization approach in synthesizing multi-beams with individual control.

In the article [14], a low-profile, wideband, high-gain antenna array is discussed for 5G mm-wave applications. The antenna is based on optimized metamaterials (MMs) and exhibits dual-beam radiation. The design incorporates a bow-tie shape operating at 28 GHz, with two bow-tie radiators based on a Substrate Integrated Waveguide (SIW) power splitter. The properly coupled resonances of the bow ties and SIW result in a wide impedance bandwidth. Additionally, a metamaterial array is integrated into the same substrate to enhance gain while maintaining a compact footprint. The antenna's gain is improved at 29 GHz using a trust-region gradient-based technique for structural dimension optimization. The experimental results demonstrate excellent agreement between the simulated and measured performance, showcasing its suitability for 5G mm-wave indoor applications. The research [15] provides a unified approach to problem-solving for allocation of resources and designing of optimal multi-beam in IoT networks that make use of satellite connectivity. They propose and implement a gaming optimisation system to reduce satellite connection latency in real time. The coalition game approach is utilized to optimize both transmission time and channel gain by arranging IoT devices. Additionally, a bisection search is employed to optimize power allocation for improved network energy efficiency. Numerical results show the superiority of the proposed technique compared to other approaches, making it applicable to various settings, including large-scale networks in real-time IoT scenarios. In paper [16], a new substrate-integrated waveguide (SIW)-based three-beam antenna for 5G applications is presented, operating in the frequency range of 28 to 32 GHz. The antenna is powered by an innovative beamforming network (BFN) that requires a single 3x3 media access control (MAC) and a 3x3 phase shifter. The proposed BFN offers a simpler and more compact design compared to the traditional Butler matrix BFN, as fewer components are required. The antenna design incorporates a multi-beam slot array antenna with beams at 40°, 0°, and -40°, optimized using HFSS. The antenna demonstrates good return loss and isolation across its operating frequency range, with measured gains ranging from 8 to 10.2 dBi. The proposed antenna has a smaller footprint compared to similar reported three-beam antennas, and the fabricated antenna's performance aligns well with the calculated results.

SUGGESTED METHODOLOGY

This research introduces a beamforming optimization technique designed to enhance the efficiency of 5G technology. The proposed technique offers a unique approach to address the challenge of optimizing beamforming configurations in 5G systems. Figure 1 illustrates the mechanism of the suggested strategy, which comprises several key components. The research begins with 5G initialization, establishing the groundwork for subsequent stages. The system model is then developed, considering various parameters and constraints relevant to beamforming optimization. The antenna beamforming stage focuses on generating and adjusting transmission beams to meet the specific requirements of the system and the desired transmission quality. The optimization phase employs advanced algorithms such as ABC, PSO, and SMO techniques to search for optimal beamforming configurations those satisfying transmission quality constraints. Finally, the performance evaluation stage assesses the achieved beamforming solutions using predefined metrics.

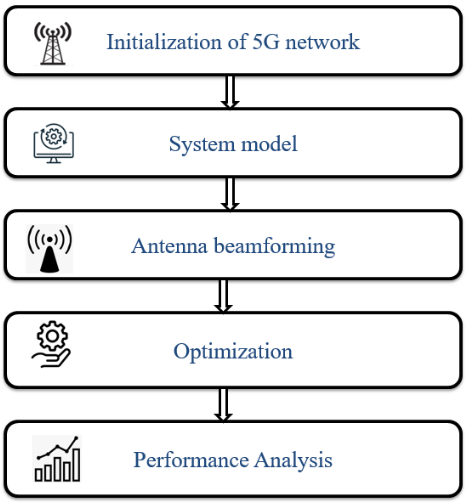

Fig. 1. Suggested Methodology Framework

A. 5G Network

The initialization of a 5G network is a critical step in ensuring the successful deployment and operation of a high-speed broadband network for public users. With the advancement of 5G technology, it has become necessary to establish a fast and efficient network infrastructure to support the transmission of data [17]. To deliver data effectively, a robust 5G network is required, capable of providing seamless connectivity and high data transfer rates. One of the key technologies employed in 5G networks is Multiple-Input Multiple-Output (MIMO) transmitters. These transmitters consist of a massive number of antenna links or components, allowing for the simultaneous broadcasting and collection of additional data [18].

By utilizing MIMO transmitters, 5G networks can enhance their capacity and overall performance. The large number of antenna links enables the network to handle a higher volume of data traffic, allowing more consumers to utilize the network simultaneously. This increased capacity benefits consumers by improving network performance and ensuring a smooth and efficient user experience. The deployment of a 5G broadband network for public users requires remote monitoring capabilities to ensure smooth operation and efficient maintenance. Remote monitoring allows network administrators to monitor the network's performance, identify potential issues, and make necessary adjustments remotely. This ensures that the network operates optimally and minimizes downtime.

B. System Model

The system model considered in this study focuses on the operation of the bottom unit, known as the gNB (gNodeB), in a 5G system. The gNB is responsible for downlink transmission [19], where data is sent from the base station to the user equipment. In this study, we propose a novel capability for the gNB, allowing it to concurrently detect the surrounding environment using a directed and adjustable beam while maintaining a separate directive wavelength for the transmission connection. By leveraging this capability, the gNB is able to optimize its beamforming process, leading to improved performance of the communication system as a whole.

In the system model, a singular sharing uniformity linear array (ULA) is employed for both transmission (TX) and reception (RX). The ULA consists of N antenna arrays that are evenly spaced at half the wavelength. This configuration enables effective beamforming and signal processing. The system also incorporates a planar waveform and considers separate RF beam formation weights for both TX and RX. These beam formation weights play a crucial role in directing the transmitted and received signals in specific directions, optimizing signal quality, and reducing interference. The system model provides a foundation for studying and optimizing beamforming techniques in the 5G downlink transmission. By incorporating adjustable beams, directional wavelength separation, and optimized RF beam formation weights, the study aims to enhance the performance and efficiency of 5G communication systems [20].

C. Antenna Beamforming

Antenna beamforming is a powerful technique used to manipulate the radiation pattern of an antenna array to achieve specific performance objectives [21]. In the case of a gNB phased-array system, the array's responsiveness is well-known and can be described by the array factor $a(\theta)$ as shown in Equation (1). This factor represents the spatial sensitivity of the array to the angle of arrival (AoA) or angle of departure (AoD) represented by RX and TX, respectively.

$$a(\theta) = [1, e^{j\pi \sin(\theta)}, \ldots . e^{j\pi (\mathrm{M}-1)\sin(\theta)}]^T \quad [1]$$

The emitted spatiotemporal pattern at time t, denoted by $X(t)$, is formed by multiplying the transmitted signal $s(t)$ with the TX beamforming vector W_{tx}, as shown in Equation (2).

$$X(t) = s(t)W_{tx} \quad [2]$$

After propagation through the air, the spatial signal interacts with objects, resulting in refraction effects. This interaction leads to the reception of a spatial waveform described by Equation (3). In this equation, $y(t)$ represents the received waveform, bk is the attenuated coefficient of the kth reflection and fD, k^t represents the proportional latency, and Doppler shift of the kth target.

$$y(t) = \sum_{k=0}^{K-1} b_k e^{2\pi j f D, k^t} a(\theta_{rx,k}) a^T(\theta_{rx,k}) X(t - T_k) + n(t) \; [3]$$

It is worth emphasizing that a high level of isolation is maintained between the transmitting (TX) and receiving (RX) devices, despite the possibility of achieving separation through realistic methods. At the receiver, beamforming techniques are utilized to combine the information received from all elements of the array. This process is illustrated in Equation (4), where W_{rx} represents the beamforming vector used for RX.

$$y(t) = W_{rx}^T y(t) \quad [4]$$

By comparing the transmitted waveform $s(t)$ with the beamformed RX waveform y, targets can be detected. The traditional method for range estimation commonly utilizes a matching filter (MF) operation. The primary goal of this operation is to optimize the signal-to-noise ratio (SNR) of the received reflection. By applying the matching filter, the SNR of the received reflection is enhanced, enabling accurate range estimation. However, alternative methodologies can also be employed, depending on the system's requirements and available computing capabilities.

In practical scenarios, the hardware platforms may impose limitations on the values of the beamforming parameters for both the TX and RX processes. Equation (5) depicts the RF beamforming parameters, where a_{rx} and β_{rx} represent the magnitude and phase values, respectively, for the nth antenna element in the RX beamforming. Similar expressions are utilized for TX beamforming. These parameters capture the specific values that can be assigned to the antenna elements considering the constraints imposed by the hardware platforms.

$$W_{rx} = [a_{rx,0} e^{i\beta_{rx,0}}, \ldots . a_{rx,N-1} e^{i\beta_{rx,N-1}}]^T \quad [5]$$

This article explores various scenarios and associated beamforming-related component designs. The first scenario assumes substantially equal and continuous amplitudes for phased-array computation. The second scenario considers more flexible designs allowing complete control over both phase and magnitude of RX and TX components. This adaptable array design offers greater customization and optimization capabilities.

In summary, antenna beamforming is a versatile technique used to shape and steer electromagnetic waves in an antenna array [22]. The phased-array system in the gNB demonstrates a recognized capability to adapt and respond effectively. It offers the flexibility to implement diverse beamforming strategies and configurations to optimize performance and fulfill specific requirements in various scenarios. This adaptability enables the gNB to tailor its beamforming operations to achieve optimal performance based on the specific needs and characteristics of each situation.

D. Optimization Approaches

We propose a two-step convex solution to effectively address the initial non-convex difficulty in time modulation beam design. To achieve this solution, the approach involves decreasing the acceptable area size for the time modulation design. In the initial phase of optimization, the primary objective is to determine the sequence's form at the central wavelength, denoted as w^0. This is done by ensuring that the specified Side Lobe Level (SLL) constraint is satisfied.

$$\begin{cases} \min_{w^0 \epsilon C^{N,1}} -real(a(\theta_0)^T V^0) \\ s.t. image(a(\theta_0)^T V^0) = 0 \\ |aa(\theta_i)^T w^0| \leq SLL.real(a(\theta_0)^T V^0), \theta_i \epsilon \Theta_{SL} \\ |V^0| \leq [1]_{N*1} \\ real(V^0) \geq [I_l.b]_{N*1} \end{cases} \quad [6]$$

Equation 6 mathematically represents this optimization, where 0 represents the primary beam direction, SL indicates the sidelobe area under consideration, SLL represents the specified SLL restriction, and $real(\cdot)$ and $imag(\cdot)$ denote the real and imaginary operations respectively. To ensure convexity in the response, the final inequality requirement approximates $|V^0|$ using $real(V^0)$.

In the second phase, based on the acquired w0 from the first phase, the goal is to further reduce the Side Band Level (SBL) by maximizing V^1.

$$\begin{cases} \min_{SBL \epsilon R^+, w^1 \epsilon C^{N,1}} SBL \\ s.t.\ |a(\theta_i)^T V^1| \leq SBL, \theta_i \epsilon \Theta_{all} \\ |aa(\theta_i)^T V^0| \leq SLL.real(a(\theta_0)^T w^0), \theta_i \epsilon \Theta_{SL} \\ |V^1| \leq |V^0|^\circ sinc(\pi\tau_{min}) \\ real(V^1) \geq |V^0|^\circ sinc(\pi\tau_{max}) \end{cases} \quad [7]$$

The optimization process described can be mathematically represented by Equation (7). In this equation, SBL represents a predefined constant that allows for some flexibility, "(all)" indicates the circular area across all dimensions, and "(°)" signifies the Hadamard derivative. To limit the range of V^0, the horizontal matrices $\tau_{min} = [\tau_{n,min}]\ NX1$ and $\tau_{max} = [\tau_{n,max}]\ NX1$ are used, and their values are determined by the equation $[n, min, n, max] = \left[\frac{|V^0 n|,|V^0 n|}{Il}\right][b, 1]$. While approximating the value of $|V^1|$ with $real(V^1)$ in the last inversion constraint maintains convexity, it results in a smaller viable solution space.

$$\frac{|w_n^1|}{|w_n^0|} = \left|\frac{\sin(\pi\tau_n)}{\pi\tau_n}\right|, I_n = \frac{w_n^1}{\tau_n}, t_n = \frac{pha(w_n^0) - pha(w_n^1) - \pi\tau_n}{2\pi} \quad [8]$$

After finding w^0 and w^1, the TMA activation I, t can be calculated using equation 8, where $pha()$ serves as the process generator.

When a specific SLL condition is provided, the convex solver effectively addresses the creation of low-side lobe time modulation beams. The optimization procedure for a 100-element constant time modulation beam formation can be completed within minutes, making it highly efficient in terms of time. However, it's important to note that certain simplifications are made in the process, which results in a reduced workable area. It may not be suitable for addressing multiple objectives or considering additional constraints beyond the specified SLL and side lobe requirements.

When dealing with a large number of Convex Time Modulated beam creation elements, such as 50 elements (75 factors), the optimization process becomes considerably more challenging. Population-relying optimization techniques require larger populations to ensure optimal solutions in complex selection areas with numerous varying factors. This increased complexity also implies greater algorithmic responsibility. When compared to other available methods, the optimization approach is regarded as one of the more effective ways to address relatively large-scale Convex Time Modulated beam creation problems, particularly when operating within limited computing resources. We use three optimization techniques like ABC, PSO and SMO. For all the algorithms first define the problems like clearly defining the objective function, decision variables, constraints, and other problem-specific details [23]. In this case, the objective function could be related to minimizing the side lobe area or maximizing the main lobe.

ABC Algorithm:

1. Initialize the colony: Create an initial population of artificial bees representing potential solutions. Each bee corresponds to a set of time modulation parameters for CTM beam creation [24].
2. Employ the employed bees phase: Each employed bee evaluates the objective function for its corresponding solution. Then, it performs a local search by generating new solutions around its current position. This can be done by perturbing the time modulation parameters within a certain range.
3. Utilize the observer bees stage: The observer bees choose solutions according to their fitness values. Solutions with higher fitness have a greater chance of being chosen. The observer bees create new solutions around the selected ones and assess their fitness.
4. Utilize the scout bees stage: The scout bees detect solutions that have not shown improvement after a specific number of iterations [25]. These solutions are discarded, and new ones are generated randomly to explore unexplored areas of the Search Space (SS).
5. Maintain the best solution: Continuously update and keep a record of the best solution discovered thus far during the iterations.

PSO Approach:

1. Initialize the swarm: Gather a swarm of particles, each of which will stand in for a different solution or set of temporal modulation parameters for making a CTM beam [26]. Initialize the particles' positions and velocities within the SS at random.
2. Compare fitness levels: Evaluate the goal function using the particle's position in the SS to determine its fitness value.
3. Optimal particle position, updated: Change the optimal position of each particle to reflect its current fitness. This is the optimal solution that the particle has found so far [27].
4. Update global best position: Identify the particle with the best fitness value among all particles in the swarm. This represents the global best solution found by the swarm.
5. Update particle velocities and positions: Update the velocities and positions of the particles based on their current positions, velocities, and the influence of their own and the global best position. This is typically done using mathematical equations that define the movement of particles in the SS, such as the velocity update equation and position update equation in PSO.

SMO Approach:

1. Initialize the spider monkeys: Create an initial population of spider monkeys, where each spider monkey represents a potential solution or a set of time modulation parameters for CTM beam creation. Randomly initialize the positions of the spider monkeys within the SS.
2. Evaluate fitness: Calculate the fitness value for each spider monkey by evaluating the objective function using its position in the SS [28].
3. Update global best position: Identify the spider monkey with the best fitness value among all spider monkeys in the population. This represents the globally best solution found by the spider monkeys.
4. Update spider monkey positions: Update the positions of the spider monkeys based on their current positions and the influence of their own and the global best position [29]. This is typically done using mathematical equations that define the movement of spider monkeys in the SS, such as the position update equation in SMO.

Until a termination requirement is fulfilled, repeat steps 2-5 for ABC and PSO, and steps 2-4 for SMO. This can be a fixed convergence threshold or an upper bound on the number of iterations required to find an optimal solution. Once the algorithm finishes, the best solution it has found should be output; this solution will be the temporal modulation parameters that will provide the best CTM beam.

RESULTS AND DISCUSSION

The advent of 5G wireless communications demands advanced antenna technologies that can support high data rates and accommodate the increased network capacity. MBAs have emerged as a potential solution due to their ability to generate multiple beams and support beamforming techniques. However, optimizing these antennas is crucial to maximize their performance. This section aims to evaluate the effectiveness of ABC, PSO, and SMO optimization techniques for MBA. The outcome of optimization techniques are tabulated in table 1.

Table 1. Comparison of optimization techniques

Techniques	Scanning Performance (%)	Scanning Loss (%)	Gain (dB)	Radiation Pattern
ABC	92	54	91	87
PSO	94.5	50	94	85
SMO	97	46	98	90

Scanning Performance: The scanning performance of the optimized MBA is crucial for effective coverage and communication. The ABC approach achieves a scanning performance of 92%, while PSO improves it further to 94.5%. Remarkably, SMO demonstrates the highest scanning performance, reaching an impressive 97%. These results indicate that all optimization techniques effectively enhance the antennas' ability to scan and cover a wide range of angles.

Scanning Loss: Reducing scanning loss is important to ensure efficient signal transmission and reception. The evaluation shows that ABC achieves a scanning loss of 54%, which is improved to 50% by PSO. SMO outperforms both techniques, achieving a scanning loss of only 46%. The lower scanning loss values indicate improved signal quality and reduced power loss during scanning. Figure 2 illustrates the scanning performance and scanning loss achieved by each optimization approach.

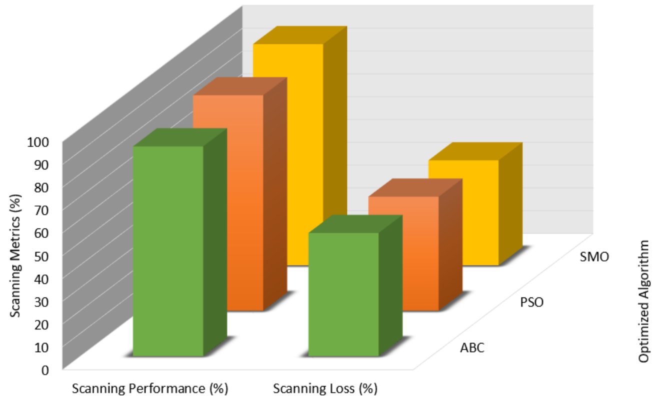

Fig 2. Scanning performance and loss analysis

Gain Analysis: The gain of an antenna directly impacts the signal strength and coverage area. The evaluation reveals that ABC optimization provides a gain of 91dB, while PSO further improves it to 94dB. Notably, SMO demonstrates the highest gain, reaching an impressive 98dB. The higher gain values achieved by all optimization techniques indicate enhanced signal strength and improved coverage. Figure 3 plots the gain values attained by each optimization technique.

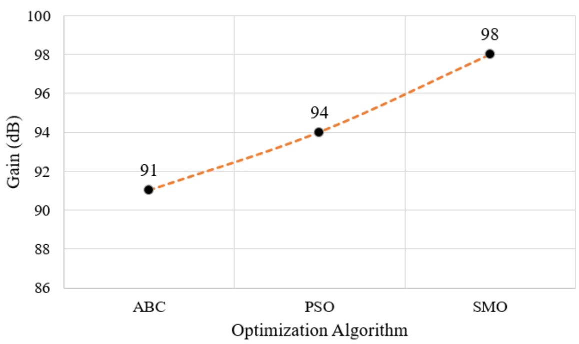

Fig 3. Comparison of gain values

Radiation Pattern: The radiation pattern of an antenna describes the distribution of radiated power in different directions. ABC optimization results in a radiation pattern with a gain of 87, while PSO achieves 85. SMO outperforms both techniques, achieving a radiation pattern with a gain of 90. These results suggest that SMO optimization leads to a more focused and efficient radiation pattern. Figure 4 illustrates the radiation pattern scores obtained by each optimization approach.

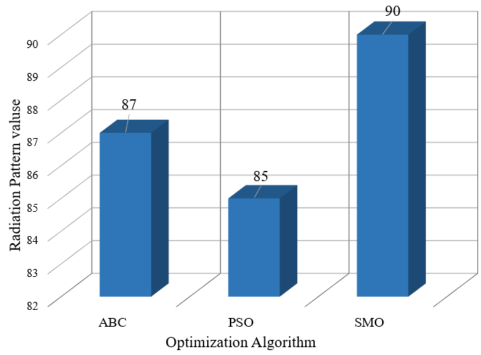

Fig 4. The outcome of radiation pattern values

CONCLUSION

In conclusion, this evaluation study on beamforming optimization techniques for multibeam antennas in 5G wireless communications demonstrated the effectiveness of three popular optimization algorithms: PSO, ABC, and SMO. The evaluation was based on scanning performance, loss, gain, and radiation pattern. Among the three techniques, SMO emerged as the winner, consistently outperforming PSO and ABC in terms of beamforming optimization. It showcased superior results in terms of above mentioned metrics. These findings highlight the potential of SMO as a preferred optimization technique for similar applications in 5G wireless communication systems.

As for future scope, further research can be conducted to explore and compare additional optimization techniques for beamforming in multibeam antennas. Additionally, investigations into the combination of different optimization algorithms or the development of hybrid approaches could potentially yield even better results. Moreover, extending the evaluation to other performance metrics and real-world scenarios would provide a comprehensive understanding of the optimization techniques' capabilities and limitations in diverse operating conditions. Such advancements will contribute to advancing the design and deployment of efficient and reliable multibeam antenna systems for 5G wireless communications.

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