Synthesis of Thinned Linear and Planar Antenna Arrays Using a Taguchi-Enhanced Binary Gold Rush Optimizer

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Abstract – In this paper, a Taguchi-enhanced binary gold rush optimizer (TEBGRO) is proposed for designing thinned antenna arrays with a low peak sidelobe level (PSLL). The method integrates the Taguchi orthogonal experimental design into the population initialization phase, generating high-quality initial populations to improve convergence speed and stability. By combining a differential mutation interference factor and a time-varying transfer function, the algorithm further balances global exploration and local exploitation capabilities. Experimental results show that TEBGRO outperforms other binary optimization algorithms for both 100-element linear arrays and 20×10 planar arrays.

Index Terms – Antenna radiation pattern, gold rush optimizer (GRO), thinned array, Taguchi method.

I. INTRODUCTION

Offering advantages such as high signal gain, strong anti-interference capability, and flexible design, antenna arrays are widely used in wireless communication, phased array radar, aerospace, and other fields [1, 2]. Thinned arrays, as compared to traditional uniform arrays, achieve smaller size and weight by selectively removing (or deactivating) certain elements, thereby reducing system costs, power consumption, and complexity of the feeding network. However, the thinning process often results in a decrease in antenna gain and an increase in peak sidelobe levels (PSLL). Thus, the optimization challenge lies in reducing the number of array elements while simultaneously decreasing PSLL.

The thinning of large-scale antenna arrays is a high-dimensional, discrete, non-linear, and non-convex problem. Over the past few decades, numerous methodologies have been proposed to reduce the number of array elements while preserving desired radiation characteristics. To this end, researchers have developed a diverse array of optimization techniques, broadly categorized into two primary classes: deterministic methods and meta-heuristic methods.While deterministic methods like the Iterative Fourier Transform (IFT) are efficient, they are prone to local optima. Meta-heuristic algorithms offer global search capabilities but often face challenges such as reliance on empirical parameter tuning and premature convergence.

To address these limitations,this paper proposes a Taguchi-enhanced binary gold rush optimizer (TEBGRO). Through three enhancement strategies, this approach improves optimization performance for thinning antenna arrays. First, the systematic reasoning capability of the Taguchi method is integrated during population initialization to generate highly representative and uniformly distributed initial solution sets. Second, the time-varying transfer function enables both the mapping of continuous values to discrete states in binary optimization and the balancing of global search with local optimization. Furthermore, a differential mutation

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interference factor is incorporated to strengthen the capability of the algorithm to escape local optima. The effectiveness of TEBGRO is validated through two case studies involving 100-element linear arrays and 20×10 planar arrays, with comparative analysis against optimization results from similar designs reported in other literature.

The main contribution of this work lies in the novel integration of the Taguchi method with the gold rush optimizer (GRO), creating the TEBGRO framework specifically for antenna array thinning. This integration features three synergistic components: Taguchi-enhanced initialization for high-quality binary sequences, a time-varying transfer function for effective continuous-to-binary mapping, and a differential mutation factor for maintaining diversity. Together, they effectively address premature convergence in this high-dimensional binary optimization problem, achieving balance between exploration and exploitation.

II. RELATED WORK

The IFT method stands as a classic deterministic technique. Leveraging the Fourier transform relationship between the array factor and the excitation distribution, this method first optimizes the array factor within the radiation pattern domain and subsequently deactivates specific elements in the aperture domain by nullifying their excitations. These two steps are executed cyclically until a thinned array configuration satisfying the requirements is obtained. While the IFT method is computationally efficient, its performance is heavily dependent on the initial solution. Furthermore, as it is essentially a gradient descent-based approach, it is prone to stagnation in local optima [3, 4].

In parallel, Genetic Algorithms (GA) [5, 6] and Ant Colony Optimization (ACO) [7] were among the earlier meta-heuristic algorithms applied to array thinning. Subsequently, Differential Evolution (DE) [8] and Biogeography-Based Optimization (BBO) [9] demonstrated superior convergence speeds. More recently, advanced algorithms such as the Fruit Fly Optimization Algorithm (FOA) [10] and Cuckoo Search Algorithm (CSA) [11] have been successfully utilized for the optimization of linear and planar arrays. These studies indicate that meta-heuristic algorithms can effectively suppress the PSLL and reduce the element count.

To synergize the strengths of distinct approaches, hybrid methods have emerged. For instance, frameworks combining the rapid convergence of IFT with the global search capability of meta-heuristics have been proposed [12]. In such frameworks, the meta-heuristic algorithm acts as a global explorer responsible for broadly scanning potential regions, while the IFT serves as a local optimizer for rapid fine-tuning; generally, the performance of these hybrid approaches surpasses that of stand-alone algorithms.

Despite the progress achieved by these methods, critical challenges persist, such as the reliance on empirical experience for parameter tuning and limited solution diversity caused by premature convergence.

Meta-heuristic algorithms, by simulating natural physical laws and biological social behaviors, perform global stochastic searches independent of gradient information. Consequently, they exhibit immense potential in solving complex non-linear and non-convex optimization problems. They have been successfully applied across numerous domains, including engineering optimization, scheduling problems, feature selection, and hyperparameter tuning for neural networks [13].

In this context, the GRO [14] has been introduced as a novel meta-heuristic algorithm mimicking the behavior of miners during the 19th-century gold rush. GRO balances exploration and exploitation by simulating the migration of miners towards affluent areas ("cooperative" behavior) and the stochastic exploration for new veins ("selfish" behavior). Characterized by a simple structure and few parameters, GRO has demonstrated outstanding performance on multiple benchmark optimization problems. Although GRO has found applications in other engineering optimization domains [15], it remains relatively new compared to mature algorithms like GA and DE, and its potential in the specific field of antenna thinning remains largely untapped. The intrinsic "cooperative" and "selfish" mechanisms of GRO provide a natural foundation for balancing exploration and exploitation, offering a solid starting point for mitigating premature convergence. Furthermore, the relatively concise structure of GRO facilitates its integration with other optimization strategies, enabling the construction of more robust hybrid models.

However, as the "No Free Lunch" theorem suggests [16], no single algorithm performs optimally on all problems. The versatility of meta-heuristic algorithms is invariably accompanied by inherent limitations. The standard GRO, when addressing high-dimensional binary thinning problems, may still be constrained by the loss of population diversity. Consequently, strategic enhancements are required to adapt GRO effectively for the antenna array thinning optimization.

III. THINNED ARRAY

A. Linear array

The structure of the linear antenna array is illustrated in Fig. 1. The array consists of $2N$ isotropic elements symmetrically arranged along the x-axis. The array factor (AF) of the linear antenna array in the x-z

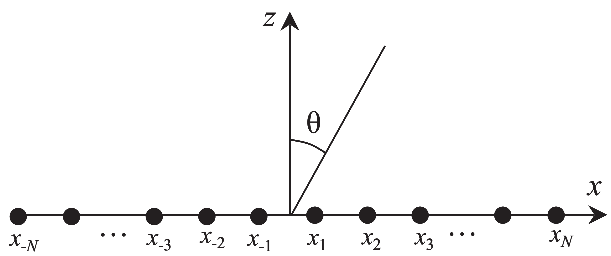

Fig. 1. Geometry of a $2N$-element symmetric linear array.

plane at an angle θ can be expressed as [17]:

$$AF(I,\theta) = \sum_{n=-N}^{-1} I_n e^{j(kx_n \sin\theta + \varphi_n)} + \sum_{n=1}^{N} I_n e^{j(kx_n \sin\theta + \varphi_n)}, \tag{1}$$

where I_n, φ_n and x_n represent the excitation amplitude, phase, and position of element n, respectively. The wave number k is defined as $k = 2\pi/\lambda$, where λ is the wavelength.

In this study, a fixed inter-element spacing of 0.5λ is utilized to mitigate mutual coupling and avoid the formation of grating lobes. $I_n = 1$ if the n-th element is "on," and $I_n = 0$ if it is "off". Assuming symmetric excitation amplitudes ($I_{-n} = I_n$), symmetric element positions ($x_{-n} = -x_n$), and zero excitation phase ($\varphi_n = 0°$). Under these conditions, the two summations in equation (1) are complex conjugates. For a fixed inter-element spacing of 0.5λ with element positions at $x_n = (n-0.5)d$ where $d = \lambda/2$, and $k = 2\pi/\lambda$, Therefore, equation (1) can be expressed as [7, 9]:

$$AF(I,\theta) = 2\sum_{n=1}^{N} I_n \cos(\pi(n-0.5)\sin\theta). \tag{2}$$

B. Planar array

Figure 2 shows the structure of the planar array, which consists of $2N \times 2M$ elements. Each element is isotropic in the x-y plane and symmetric about the x and y axes. Under the same conditions as a linear array, the AF is given by [7, 9]:

$$AF(I,\theta,\varphi) = 4\sum_{n=1}^{N}\sum_{m=1}^{M} I_{nm} \cos(\pi(n-0.5)\sin\theta\cos\varphi) \cdot \cos(\pi(m-0.5)\sin\theta\sin\varphi), \tag{3}$$

where θ is the elevation angle relative to the z-axis and φ is the azimuth angle relative to the x-axis. I_{nm} represents the excitation amplitude, which takes a value of 0 or 1. The array elements in the other three quadrants can be obtained symmetrically based on the position of the array elements in the first quadrant.

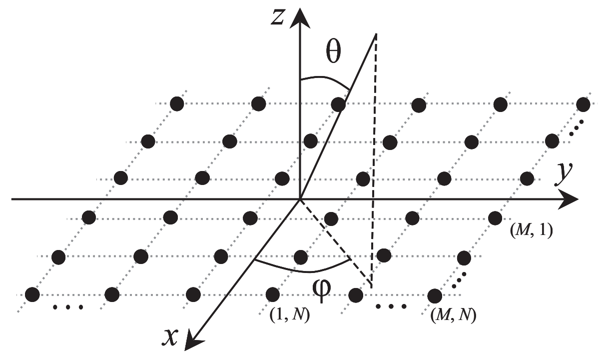

Fig. 2. Geometry of a $2N \times 2M$-element symmetric planar array.

C. Fitness function

As an important performance indicator of array antennas, the expression of PSLL is:

$$PSLL = \max_{\forall\theta\in S}\left(20\log\left|\frac{AF(I,\theta)}{AF_{\max}}\right|\right), \tag{4}$$

where S denotes the side lobe region excluding the main beam and $AF_{\max}$ is the peak of main beam.

To suppress the PSLL, the fitness function is defined as:

$$Fitness = PSLL. \tag{5}$$

The optimization goal is to minimize this Fitness value.

For planar antenna arrays, the fitness function is determined by the higher PSLL value between the $\varphi = 0°$ and $\varphi = 90°$ planes, which can be expressed as:

$$Fitness = \max(PSLL|_{\varphi=0°}, PSLL|_{\varphi=90°}). \tag{6}$$

IV. THE TAGUCHI-ENHANCED BINARY GOLD RUSH OPTIMIZER

A. Taguchi method

Based on statistical experimental design, the Taguchi method systematically optimizes product robustness through parameter design. It employs two core components: orthogonal arrays (OA) for efficient multi-factor analysis and the signal-to-noise ratio (SNR) to measure robustness. Using OA, the method reduces experiments while preserving statistical validity. Meanwhile, the SNR evaluates parameter stability against noise factors. Therefore, this method has been applied to various optimization problems [18–20]. To facilitate understanding, three key concepts used in this paper are defined as follows:

Levels: These represent the specific values assigned to the design variables. In the context of array synthesis, if a variable represents the excitation amplitude or element position, the "levels" are the candidate values selected for evaluation in each iteration.

OA: It is utilized here as a local search mechanism. The OA is dynamically constructed based on two candidate solutions randomly selected from the current initial population. Each column of the OA represents a dimension (i.e., a binary bit) where the parent vectors differ in value, while each row signifies a new candidate solution formed by the combination of the bit values from the parent vectors.

SNR: It is no longer used to measure robustness; instead, its mathematical form is adopted as a deterministic selection criterion to identify the optimal binary value for each feature dimension. For every position where the two parent solutions differ, the SNR values corresponding to both levels are calculated separately.

Traditional GRO employing random initialization often exhibit poor population diversity and inadequate solution space exploration. This study enhances population initialization by incorporating the Taguchi method.

First, randomly select two individuals, b_1 and b_2, from the initial population. The chance of selecting two individuals with a Hamming distance of 1 is low, and even if this occurs, the negative impact remains relatively limited. The built-in diversity preservation mechanisms in TEBGRO ensure that the search process promptly recovers and continues progressing toward the global optimum. If they differ at w bit positions, a corresponding two-level OA is generated. For each factor $i(i = 1,2\ldots,w)$ in this OA, the standard levels (1 and 2) are substituted with the respective bit values from b_1 and b_2, yielding a modified OA tailored to these individuals.

Subsequently, the SNR is calculated for each run in the modified OA. The use of SNR adapts the classical concept for computational optimization, and it serves as a ranking metric (not a robustness measure) to select the optimal element combination from OA tests based on PSLL performance. Given that the objective function consistently produces negative values, the "smaller-the-better" quality characteristic is adopted for SNR computation, defined as:

$$SNR = -10\log\left(\frac{1}{N_r}\sum_{i=1}^{N} y_i^2\right), \tag{7}$$

where N_r is the number of rows (experimental runs) in the OA, and where y_i is the fitness value (PSLL) obtained from the i-th experimental run.

The construction of the initial population proceeds as follows: in each iteration, two parent solutions are randomly selected. The Taguchi method, utilizing an orthogonal array and the SNR criterion, is then applied to this pair to systematically generate a single, high-quality offspring. This offspring is derived from the optimal combination of the parents' differing element states and is directly accepted into the new population. This iterative process of "select-pair-generate-accept" continues until the newly formed population reaches the predefined target size, ensuring a high-performing starting point for the subsequent optimization.

B. Differential mutation interference factor

The GRO often exhibits limitations when dealing with complex, high-dimensional problems. These include insufficient population diversity during later iterations and limited convergence accuracy. To mitigate these issues, a differential mutation interference factor is incorporated into the cooperative search phase of GRO, formulated as:

$$X(t+1) = X(t) + r\cdot(X_{g2}(t) - X_{g1}(t)) + \gamma, \tag{8}$$

where $X(t+1)$, $X(t)$, and t represent the new position of the feasible solution, current solution and iteration count, respectively. $X_{g2}(t)$ and $X_{g1}(t)$ are two randomly selected gold mining prospectors, r is a random number between [0, 1], and γ is the differential mutation interference factor, represented as:

$$\gamma = \delta\cdot(X_{best}(t) - X(t)), \tag{9}$$

where $X_{best}(t)$ is the current optimal solution, and δ is the adaptive mutation factor, represented as:

$$\delta = \delta_0\cdot 2^{\varepsilon}, \tag{10}$$

$$\varepsilon = \exp\left(1 - \frac{t_{\max}}{t_{\max}+1-t}\right), \tag{11}$$

where δ_0 is the mutation parameter, set to 0.5 in this case. This value was determined through testing and was found to provide an effective trade-off, offering sufficient perturbation without compromising convergence stability. The adaptive nature of δ further reduces dependence on its initial value. The adaptive mutation factor δ starts at $2\delta_0$ and decreases gradually throughout the optimization process, approaching δ_0 as the iteration count reaches the maximum, enabling TEBGRO to more easily escape local optima and avoid premature convergence [21].

C. Time-varying transfer function

GRO and all its operations are based on evaluating solutions using real-valued variables in a continuous search space, which cannot be directly applied to

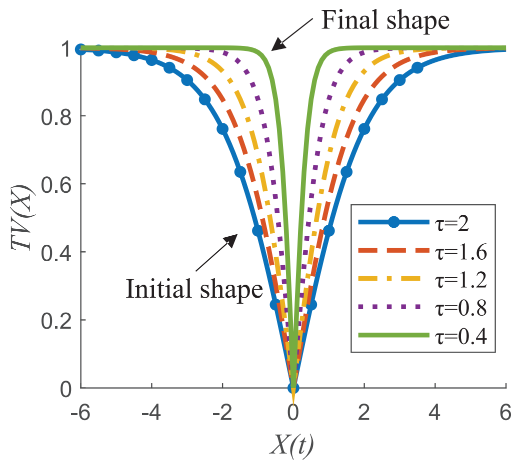

Fig. 3. Demonstration of time-varying transfer function during iteration when $\tau_{\max} = 2$ and $\tau_{\min} = 0.4$.

solve thinned optimization problems for array antennas. Therefore, it is necessary to transform these operations to make them applicable to the binary search space.

Transfer functions effectively convert continuous algorithms into binary ones. The transfer function is independent of the algorithm, does not affect the search behavior of the algorithm, and does not change the computational complexity of the algorithm. A transfer function can play a crucial role in both the exploration and exploitation phases of an optimizer, not just converting a continuous search space into a binary search space [22, 23].

Optimization algorithms should initially prioritize exploration to avoid local optima, transitioning to exploitation in later stages to enhance solution quality. If the transfer function remains unchanged throughout the optimization process, it cannot provide enough diversity, leading to an imbalance between exploration and exploitation. These limitations can be addressed by introducing a time-varying transfer function [24, 25], expressed as follows:

$$TV(X(t)) = \left| \tanh\left(\frac{X(t)}{\tau}\right) \right|, \tag{12}$$

$$X(t+1) = \begin{cases} 1, & r < TV \\ 0, & r > TV \end{cases}, \tag{13}$$

where $TV(X(t))$ is the time-varying transfer function, τ is the time-varying control parameter, which starts from an initial value and gradually decreases with iterations. This is achieved by the following:

$$\tau = \tau_{\max} - t\left(\frac{\tau_{\max} - \tau_{\min}}{t_{\max}}\right), \tag{14}$$

where $\tau_{\max}$ and $\tau_{\min}$ are the bounds on the control parameter τ. The shape of the transfer function changes over time to smoothly transition from the exploration phase to the exploitation phase, depending on different values of τ, as shown in Fig. 3. Here, $\tau_{\max}$ is set to 2, and $\tau_{\min}$ is set to 0.4. A $\tau_{\max}$ larger than 2 would overly flatten the transfer function, inhibiting exploration by preventing $TV(X)$ from approaching 1. A $\tau_{\min}$ smaller than 0.2 would render the transfer function too steep, pushing $TV(X)$ to 1 for most inputs and preventing stable convergence.

To more intuitively illustrate the execution steps of TEBGRO, the flowchart of the improved algorithm is depicted in Fig. 4.

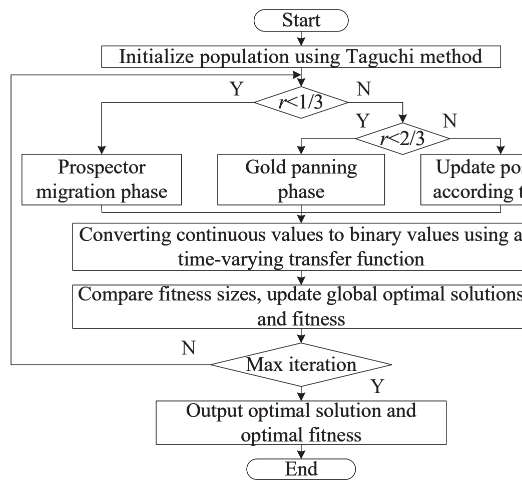

Fig. 4. Flow chart of TEBGRO for array thinning optimization.

V. NUMERICAL RESULTS

In this section, several numerical results are presented to demonstrate the effectiveness of TEBGRO. To ensure a fair comparison, the performance of TEBGRO is evaluated against the best-reported results from the cited literature for the identical linear and planar array specifications.

A. Linear array

The first scenario discusses a 100-element thinned linear array that is symmetrical along the x-axis, with each element spaced at 0.5λ and centered at the origin.

The distribution of excitation amplitude is symmetrical with respect to the center of the linear array, so only half of the amplitude needs to be optimized. The initial population size of TEBGRO is set to 50, and the maximum iteration limit is 300. The optimal value is obtained by running independently for 50 times.

Figure 5 illustrates the distribution of elements in the optimal linear array and provides a comparison of the radiation patterns between the full array and TEBGRO. The PSLL values for TEBGRO and the full array are

−21.29 dB and −13.23 dB, respectively. The thinned array demonstrates a significant reduction in PSLL while concurrently decreasing the number of elements compared to the full array.

Table 1 presents the optimization results of the linear array obtained using TEBGRO. For comparison, the thinning results of the linear arrays obtained by BBO [9], ACO [7], and MICZT [4] are also included in Table 1. The PSLL values for BBO, ACO, and MICZT are −20.84 dB, −20.52 dB, and −21.13 dB, respectively. Among these results, TEBGRO exhibits the lowest PSLL, indicating that it achieves a higher convergence accuracy in the optimization of a linear array with 100 elements.

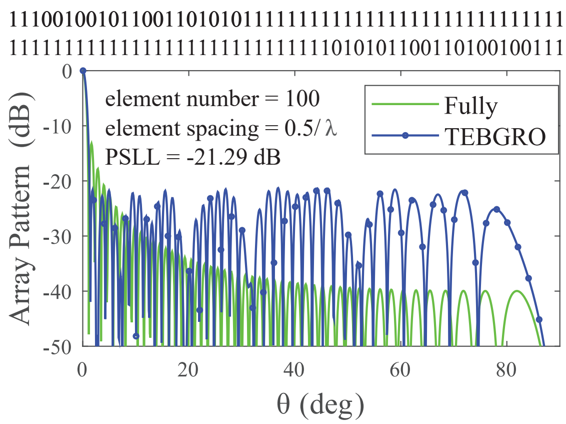

Fig. 5. Element distribution of the optimal linear array and comparison of radiation patterns: Full vs. TEBGRO.

Table 1: Comparison results of linear array

Algorithm	TEBGRO	BBO [9]	ACO [7]	MICZT [4]
PSLL (dB)	−21.29	−20.84	−20.52	−21.13
% of thinning	20	22	20	20

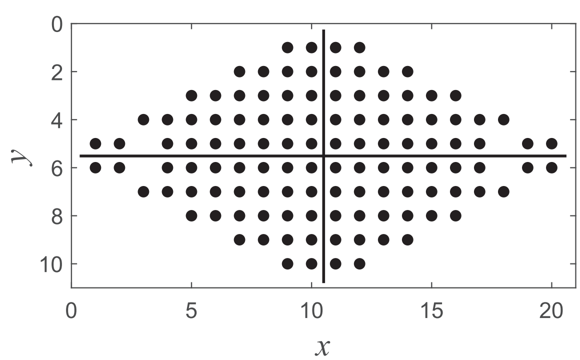

Fig. 6. Element distribution of the optimal planar array.

B. Planar array

In the second example, a planar array with 20 × 10 elements is used for thinning, and the PSLL is suppressed in the $\varphi = 0°$ and $\varphi = 90°$ planes. The excitation amplitude distribution of the planar array exhibits symmetry with respect to the coordinate axes, allowing for optimization of only a quarter of the array. All other experimental parameters remain consistent with those in the initial example.

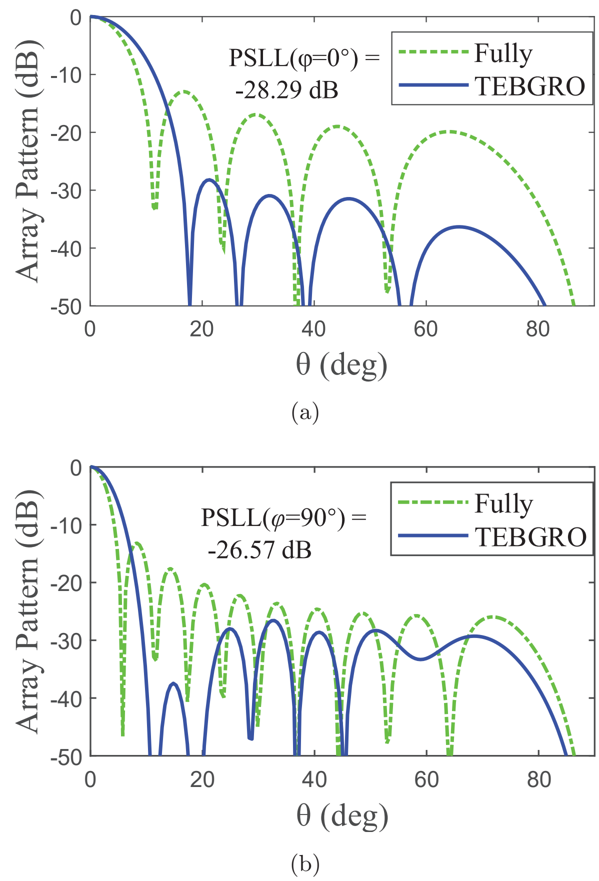

Fig. 7. Planar array radiation pattern comparison (Full vs. TEBGRO) in the (a) $\varphi = 0°$ and (b) $\varphi = 90°$ planes.

Figure 6 illustrates the element distribution of the optimized planar array. For the azimuth angles $\varphi = 0°$ and $\varphi = 90°$, the corresponding radiation patterns of the full array and the TEBGRO optimized array are compared in Fig. 7. The optimization successfully reduced the number of array elements from 200 to 116, while simultaneously lowering the PSLL by 15.33 dB (for the $\varphi = 0°$ plane) and 13.38 dB (for the $\varphi = 90°$ plane).

The same planar array was designed using M-cGA, BDE, and ACO in [6, 8], and [7], respectively. In order to further verify the performance of TEBGRO, the optimal results obtained from TEBGRO, M-cGA, BDE, and ACO are listed in Table 2. The corresponding entry in Table 2 remains blank due to the undisclosed array element arrangement in [6].

In the $\varphi = 0°$ plane, TEBGRO achieved a PSLL of −28.29 dB, outperforming the values of −26.6 dB,

Table 2: Comparison results of planar array

Algorithm	TEBGRO	M-cGA [6]	BDE [8]	ACO [7]
$PSLL\|_{\varphi=0^\circ}$ (dB)	−28.29	−26.6	−26.09	−25.76
$PSLL\|_{\varphi=90^\circ}$ (dB)	−26.57	−23.8	−25.09	−25.67
% of thinning	42	–	46	32

−26.09 dB, and −25.76 dB reported in [6, 8], and [7], respectively. Similarly, in the $\varphi = 90^\circ$ plane, the PSLL obtained with TEBGRO was −26.57 dB, which is superior to the corresponding values of −23.8 dB, −25.09 dB, and −25.67 dB from the same references. In both evaluated planes, TEBGRO consistently yielded the lowest PSLL. The planar array results again demonstrate that TEBGRO is an effective thinned array optimization technique.

VI. CONCLUSION

This paper presents the design of thinned antenna arrays using TEBGRO, aiming to reduce the number of array elements while minimizing PSLL. To enhance optimization convergence speed and precision, three improvement strategies are proposed: the Taguchi method, time-varying transfer function, and differential mutation interference factor. For a 100-element thinned linear array, TEBGRO achieves a PSLL of −21.29 dB. In the case of a 20×10 thinned planar array, the algorithm obtains a PSLL of −28.29 dB at $\varphi = 0^\circ$ and −26.57 dB at $\varphi = 90^\circ$. The results outperform other binary algorithms, demonstrating TEBGRO's superior optimization capability for array thinning.

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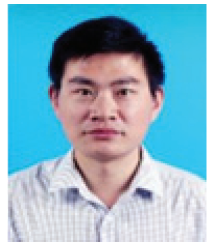

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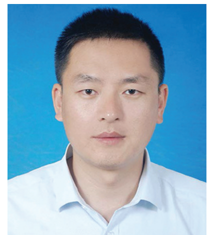

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