Application and Analysis of the Multi-Strategy Enhanced Grey Wolf–Particle Swarm Hybrid Algorithm in Radio-Antenna Array Optimization*

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Abstract

The Peak Side Lobe Level (PSLL), sensitivity, and directivity of a radio antenna array directly determine the system performance in weak-signal detection, anti-interference, and resolution. In applications from the High Frequency (HF) to Very High Frequency (VHF) bands, uniform arrays suffer from excessively high sidelobes and are prone to grating lobes during wide-angle scanning, while traditional sparse-array optimization algorithms are susceptible to premature convergence and entrapment in local optima. To address these issues, this study proposes a Multi-strategies Enhanced Grey Wolf Optimization-Particle Swarm Optimization (MEGWO-PSO) algorithm for sparse optimization of two-dimensional planar arrays. The algorithm adopts a two-stage framework of "global exploration-local refinement" : in the first stage, an enhanced grey wolf algorithm incorporating a double-order S-shaped attenuation convergence factor and adaptive crossover mutation is used to achieve efficient global search and avoid premature convergence; in the second stage, the optimized search space is used as the initial input, and local refinement is performed through an improved particle swarm optimization algorithm. Simulations are conducted with the sum of the PSLLs in the azimuth and elevation cuts as the optimization objective. The results show that MEGWO-PSO can effectively design 100-element small- and medium-scale arrays, achieving a PSLL improvement of 9.39 dB over that in the literature. For a 256-element large-scale array, considering the key performance parameters of radio antenna arrays, its PSLL is reduced by 13.22 dB, 21.32 dB, and 14.64 dB compared with grey wolf optimization, particle swarm optimization, and genetic algorithms, respectively, while the sensitivity is improved by 10%, 24.8%, and 25.6%, respectively. Moreover, the optimized array achieves superior PSLL suppression at different scanning angles, with maximum reductions of 34.79 dB and 15.63 dB compared with the uniform array and the grey-wolf-optimized sparse array, respectively. This study provides a technical approach and support for meeting the requirements of large aperture, high performance, and wide-angle scanning in radio telescopes.

Full Text

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Application and Analysis of the Multi-Strategy Enhanced Grey Wolf-Particle Swarm Hybrid Algorithm in Radio-Antenna Array Optimization*

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Abstract The peak side lobe level (Peak Side Lobe Level, PSLL), sensitivity, and directivity of a radio-antenna array directly determine the system' s weak-signal detection, anti-interference, and resolution performance. In applications from high frequency (High Frequency, HF) to very high frequency (Very High Frequency, VHF), uniform arrays have problems such as excessively high side lobes and the tendency for grating lobes to appear during wide-angle scanning, while traditional sparse-array optimization algorithms are prone to premature convergence and falling into local optima. To this end, this study proposes a multi-strategy enhanced grey wolf optimization–particle swarm optimization (Multi-strategies Enhanced Grey Wolf Optimization-Particle Swarm Optimization, MEGWO-PSO) algorithm for two-dimensional planar-array sparse optimization. The algorithm adopts a two-stage framework of "global exploration–local refinement": in the first stage, an enhanced grey wolf algorithm incorporating a two-stage S-shaped attenuation convergence factor and adaptive crossover mutation is introduced to achieve efficient global search and avoid premature convergence; in the second stage, the optimized search space is used as the initial input, and local refinement is carried out by an improved particle swarm algorithm. Simulations are performed with the sum of the PSLLs in the azimuth and elevation cuts as the optimization objective. The results show that MEGWO-PSO can effectively design a 100-element small-to-medium-scale array, with the PSLL improved by 9.39 dB compared with that in the literature; for a 256-element large-scale array, considering the key performance parameters of a radio-antenna array, its PSLL is reduced by 13.22 dB, 21.32 dB, and 14.64 dB compared with the grey wolf, particle swarm, and genetic algorithms, respectively, and the sensitivity is improved by 10%, 24.8%, and 25.6%, respectively. Moreover, after optimization, the array has better PSLL suppression at different scan angles, with reductions of up to 34.79 dB and 15.63 dB compared with a uniform array and a grey-wolf-optimized sparse array, respectively. This study provides a technical approach and support for meeting the needs of radio telescopes for large aperture, high performance, and wide scanning.

Keywords Method: multi-strategy enhanced grey wolf–particle swarm hybrid optimization (MEGWO-PSO) algorithm; Instruments: sparse array, sensitivity; Techniques: peak side lobe level; Techniques: wide-angle scanning

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1 Introduction

In the fields of modern wireless communications, radar, and radio astronomy, planar antenna arrays have become a core component[1] and an important system architecture because they can readily realize multi-beam, phased scanning, and programmable beamforming capabilities.

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Traditional uniformly distributed antenna arrays usually adopt half-wavelength spacing to avoid grating lobes. However, in high-frequency bands, the wavelength becomes shorter. To maintain the aperture size of the array, a large number of elements must be deployed, which leads to obvious performance limitations during wide-angle beam scanning: the sidelobe level increases and grating-lobe effects appear[2–3]. The resulting drawbacks have become increasingly prominent, seriously restricting the performance of antenna systems. Especially in the field of radio astronomy, the design performance of antenna arrays —such as directivity, gain, and sidelobe level—directly determines the reliability and observational efficiency of the entire system[4]. In particular, for high-frequency (High Frequency, HF, 3–30 MHz) to very-high-frequency (Very High Frequency, VHF, 30–300 MHz) antenna arrays, scientific demand continues to grow. How to control their scale and cost while ensuring array performance has become an important issue[5]. In this frequency band, in order to obtain a sufficiently large array aperture to improve sensitivity and spatial resolution, traditional uniform arrays are usually arranged with half-wavelength spacing referenced to a certain frequency. However, because the aperture size is closely related to the operating wavelength, when the operating frequency increases and the wavelength decreases, grating-lobe effects occur, causing the observational performance of the antenna array to decline sharply[6]. Representative arrays in this field, such as the Low Frequency Array (LOFAR)[7–8] and the Square Kilometre Array (SKA)[9–11], have faced severe engineering and technical challenges during construction and operation. To effectively detect weak radio signals from the universe and obtain high-quality imaging, astronomers

Fig. 1 Sparse antenna distribution of LOFAR-LBA 96 element[8]

Figure 1: Fig. 1 Sparse antenna distribution of LOFAR-LBA 96 element[8]

need to build antenna arrays with huge effective apertures to improve sensitivity, while also possessing the ability to perform wide-angle scanning, so as to realize observational systems with large fields of view and high resolution[12].

To break through this technical bottleneck, the sparse planar antenna array has been proposed and applied in layout studies of radio antenna arrays[13]. In studies at home and abroad, LOFAR adopts a randomly exponentially distributed sparse layout in the LBA (Low Band Antenna, 10–80 MHz) band[8], as shown in Fig. 1. The design of the LWA (Long Wavelength Array) incorporates directional-pattern synthesis optimization into sparse arrays, with the objective of reducing secondary sidelobe levels or increasing the number of sampling points in the spatial-frequency domain[14-15]. Among these studies, Kogan and Cohen[16] optimized an elliptical array for LWA-1 by iteratively adjusting the positions of 256 elements (initially in a standard hexagonal layout). Taking the peak sidelobe level (PSLL) as the optimization objective, and using the element spacing S and the array-area region as constraints, they optimized the antenna array and determined a sparse layout, as shown in Fig. 2.

The core idea of sparse optimization is to perform nonuniform optimization of element positions, breaking the periodic spatial distribution of radiated energy so as to eliminate grating lobes, and thereby achieving radiation performance comparable to, or even better than, that of a uniform array with a specified number of elements[17]. This optimization can not only reduce the peak sidelobe level, but also significantly lower the system complexity of the array and improve the reliability and efficiency of the antenna system. This provides great convenience for the realization of future large-scale, high-performance radio astronomy arrays. The layout optimization process is essentially a nonlinear, nonconvex combinatorial optimization problem[18]. Its complexity is mainly reflected in the fact that the relationship between the objective function (for example, PSLL) and the element positions is highly nonlinear, and there exist a large number of local optimal solutions, making the solution process difficult to carry out using traditional deterministic methods. Therefore, research and development of efficient and intelligent optimization algorithms to find optimal element layouts in complex and vast search spaces has important theoretical and practical value for the design and engineering application of antenna arrays in radio astronomy[19].

Fig. 1 Sparse antenna distribution of LOFAR-LBA 96 element[8]

For a long time, layout optimization of sparse arrays has mainly relied on traditional mathematical optimization methods and meta-heuristic algorithms[20]. Early studies mostly adopted deterministic methods, such as the Newton method, gradient descent, and quadratic programming. Although these methods can obtain accurate solutions under specific conditions, they are highly

Fig. 2

Figure 2: Fig. 2

dependent on the selection of initial values and are prone to becoming trapped in local extrema; thus, they cannot effectively handle nonconvex optimization problems[21]. In addition, the computational complexity of these algorithms increases sharply as the array scale expands, making them difficult to apply to large-scale array optimization. With the rapid development of intelligent computing, various

As metaheuristic algorithms inspired by phenomena in the natural world, owing to their strong global search capability and their lack of requirements for differentiability of the objective function, they have been widely applied in the field of array optimization.

Figure 2 Layout of the optimized LWA-1 antenna array. Panel (a): original regular layout; panel (b): optimized irregular sparse layout[^16].

Fig. 2 Layout with optimized LWA-1 antenna array, panel (a): original regular layout, panel (b): optimized irregular sparse layout[^16].

Among them, the genetic algorithm (Genetic Algorithm, GA)[^19][^22-^24] simulates the selection, crossover, and mutation operations in biological evolution, and demonstrates excellent global search capability in dealing with complex multimodal optimization problems. The particle swarm optimization (Particle Swarm Optimization, PSO)[^1][^25-^26] algorithm has attracted much attention because of its simple implementation and fast convergence speed, and is especially suitable for continuous optimization problems.

In addition, a variety of new optimization algorithms have emerged in recent years, such as the grey wolf optimizer (Grey Wolf Optimizer, GWO)[^27-^28], proposed in 2014 by the Australian scholar Mirjalili et al.[^29]. By simulating the social hierarchy and group-cooperative hunting mechanism of grey wolves in nature, this algorithm constructs an optimization process of "encircling–pursuing–attacking," thereby efficiently searching for the optimal solution over the global range[^28]. Because of its simple structure, few parameters, fast convergence speed, and prominent global optimization capability, GWO has in recent years been widely applied to the solution of complex optimization problems. In addition, the whale optimization algorithm (Whale Optimization Algorithm, WOA)[^30] and the salp swarm algorithm (Salp Swarm Algorithm, SSA)[^31] have also achieved significant results in optimization problems. However, these single metaheuristic algorithms generally have their own limitations: although the GA algorithm has strong global search capability, its convergence speed is slow in the later stages of iteration and its solution accuracy is limited[^27]; the PSO algorithm, because its update formula relies heavily on the individual optimum and the swarm optimum, when handling high-dimensional or multimodal functions, can easily fall into a local optimum because of "premature convergence" [^1]. Although the GWO algorithm has a certain balance between exploration and exploitation, the singularity of its convergence factor and position-update mechanism means that, on complex problems, it may still fall into premature convergence, leading to insufficient population diversity and making it difficult to find the true global optimum[^28].

To overcome the inherent defects of single algorithms, researchers have begun to explore the fusion of the advantages of different algorithms, developing various hybrid or multi-strategy algorithms. For example, some scholars have introduced the crossover and mutation operations of GA into PSO to enhance its population diversity[^32]; other studies have combined the jump-out mechanism of simulated annealing with the particle swarm algorithm[^33]. Although these hybrid algorithms improve optimization performance to a certain extent, their fusion strategies are mostly simple series or parallel combinations, lack deep collaborative mechanisms, and make it difficult to achieve a perfect dynamic balance between global exploration and local exploitation[^32]. In addition, some hybrid algorithms have relatively high design complexity and difficult parameter adjustment, and still face the problem that convergence speed and solution accuracy are hard to reconcile[^34]. How to construct a hybrid optimization algorithm that can truly realize complementary advantages and has a good optimization effect remains a current research hotspot and difficulty in the field of array optimization.

In response to the above challenges, this paper proposes a multi-strategy enhanced 型

Gray Wolf-Particle Swarm (Multi-strategy Enhanced GWO-PSO, MEGWO-PSO) hybrid optimization algorithm, aiming to provide an efficient and stable solution for the layout of sparse planar antenna arrays in radio astronomy. This algorithm adopts a two-stage collaborative optimization framework of "global exploration–local refinement," and on this basis incorporates multiple adaptive and enhancement mechanisms, integrating and complementing the global convergence capability of GWO with the local fine-search advantage of PSO. Specifically: in the first stage, the improved gray wolf optimization algorithm introduces a two-stage S-shaped attenuation convergence factor, and integrates the enhanced adaptive crossover and mutation operations of the genetic algorithm, effectively improving population diversity and global search capability; in the second stage, the algorithm uses the final population of the first stage as the initial input of the second stage (improved particle swarm optimization), realizes "warm start," and introduces an adaptive-attenuation random perturbation term δ to improve the particles' local optimization capability and their ability to escape local optima. Through this staged, multi-strategy collaborative hybrid optimization mode, the algorithm balances exploration and exploitation, achieving rapid convergence and high-precision solution in complex optimization problems.

In this paper, Section 2 introduces the mathematical model of sparse planar antenna array layout and the meanings of the physical parameters in the opti-

Fig. 3 The schematic diagram of the planar array

Figure 3: Fig. 3 The schematic diagram of the planar array

mization. Section 3 elaborates the MEGWO-PSO hybrid algorithm model and implementation process, including its key improvement strategies and mathematical description. Finally, Section 4 conducts simulation design and verification of the algorithm in optimizing peak sidelobe level, sensitivity performance variation, and coping with multi-azimuth scanning; the simulation results verify the advantages of the algorithm in global optimization capability, convergence speed, and solution accuracy.

2 Two-Dimensional Planar Array Pattern Modeling and Key Parameters

2.1 Planar Array Pattern Modeling

In a rectangular planar antenna array, two spacing values are required to represent the inter-element spacing. The spacing in the x direction is denoted as d_x, and the spacing in the y direction is denoted as d_y. The number of elements in the x direction is denoted as M, the number of elements in the y direction is denoted as N, and z is the radiation direction; thus, the total number of array elements is $M \times N$ [19]. Then the coordinates of any array element N_{mn} can be expressed as (x_m, y_n). A schematic diagram of its antenna element distribution is shown in Fig. 3, where θ and ϕ are the azimuth angle and elevation angle, respectively.

According to the coherent superposition theorem [19], the expression of the two-dimensional array pattern is:

$$F(\theta,\phi) = \sum_{m=1}^{M}\sum_{n=1}^{N} \mathrm{e}^{\mathrm{j}\frac{2\pi}{\lambda}[(x_m \sin\theta\cos\phi + y_n \sin\theta\sin\phi) - (x_m \sin\theta_0\cos\phi_0 + y_n \sin\theta_0 \sin\phi_0)]}, \tag{1}$$

where j is the imaginary unit, and λ is the wavelength (unit: m); (θ_0, ϕ_0) are the beam scanning pointing angles of the array, i.e., the scanning-angle parameters.

Fig. 3 The schematic diagram of the planar array

2.2 Fitness Function Construction

Sidelobes (also called minor lobes) are secondary radiation beams in the array-antenna pattern other than the main lobe. Their characteristics characterize the antenna' s ability to receive interference signals in non-main-radiation directions. In technical specifications, the normalized PSLL, usually characterized by a decibel value, is adopted as a core evaluation parameter.

As an important performance-index parameter of array antennas, PSLL can be optimized by intelligent optimization algorithms for the element positions of sparse rectangular planar array antennas considering multiple constraints, so that the PSLL of the array radiation pattern is optimal. Its value is the ratio of the maximum sidelobe radiation intensity to the maximum main-lobe radiation intensity. This index has important reference value for evaluating the performance of sparse array systems, and is also one of the important parameters that must be considered in the optimization of this paper. It is as follows:

$$\mathrm{PSLL} = 20 \lg \frac{F_{\mathrm{sm}}}{F_{\max}}, \qquad (2)$$

where PSLL is the peak sidelobe level; F_{sm} represents the maximum value of the sidelobes in the normalized pattern; and $F_{\max}$ represents the maximum value of the main lobe in the normalized pattern.

This study takes the maximum PSLL as the optimization objective. Considering the observational requirements of radio astronomy, the fitness function is taken as the sum of the peak sidelobe levels of the pattern in the azimuth-direction cut ($\theta = \theta_0$) and the elevation-direction cut ($\phi = \phi_0$). Through the positive ···

search for sidelobes in the cross directions. The obtained PSLL is the sidelobe peak value in the principal observation directions, and may be slightly lower than the global maximum sidelobe value obtained by a full-space three-dimensional search. However, the variation trends of the two are highly consistent, and the magnitude of the deviation does not affect the ranking of the merits of sparse-optimization schemes or the performance evaluation. Therefore, the PSLL values in these two directions are used to reflect the overall sidelobe-level condition:

$$\begin{aligned} f(\theta,\phi) &= \max\left[F_{\mathrm{dB}}(\phi,\theta_0)\right] + \max\left[F_{\mathrm{dB}}(\phi_0,\theta)\right] \\ &= \mathrm{PSLL}(\phi,\theta_0) + \mathrm{PSLL}(\phi_0,\theta). \end{aligned} \qquad (3)$$

Because the fitness functions adopted in this paper are all taken as absolute values, the sparse-optimization problem is transformed into the problem of finding the maximum value of the fitness function. That is,

$$\mathrm{fit} = \mathrm{PSLL} = \max\{|f(\theta,\phi)|\}. \qquad (4)$$

2.3 Key Evaluation Parameters of Radio Telescope Array Performance

Sensitivity is a key performance indicator for radio astronomical observation. This section specifically introduces the sensitivity calculation formulas used in the quantitative analysis in this paper.

(1) Directivity factor and gain

The directivity factor is calculated as

$$D(\theta,\phi)=\frac{4\pi F^2(\theta,\phi)}{\displaystyle\int_0^{2\pi}\int_0^{\pi}F^2(\theta,\phi)\sin\theta\,d\theta d\phi}. \tag{5}$$

The expression for antenna gain is

$$G(\theta,\phi)=eD(\theta,\phi), \tag{6}$$

where e is the total antenna efficiency and $D(\theta,\phi)$ is the directivity factor. Antenna gain directly determines the size of the effective area of the antenna.

(2) Effective area

The effective antenna area is the effective cross-sectional area characterizing the antenna' s reception of electromagnetic waves, and is one of the core parameters determining the numerical value of antenna sensitivity. Its calculation formula is as follows:

$$A_\mathrm{e}=\frac{\lambda^2}{4\pi}G. \tag{7}$$

(3) Sensitivity

Sensitivity is an important parameter characterizing the observing capability of a radio telescope, and is also the core evaluation index of the sparse-optimization scheme for the radio array in this paper. It directly determines the ability of the radio telescope receiving system to detect weak signals [35]. In the field of radio astronomy, the unit of sensitivity is the jansky (Jy); the lower this value, the higher the sensitivity performance, that is, the better the radio telescope' s observational performance. The calculation formula is as follows:

$$S_\mathrm{min}=\frac{KT_\mathrm{sys}}{A_\mathrm{e}\sqrt{tB}}, \tag{8}$$

where T_sys is the system temperature, in kelvin (K); B is the observing bandwidth, in hertz (Hz); and t is the integration time, in seconds (s). These three parameters are related to the antenna elements and the back-end receiver. Since this paper considers only the influence of antenna layout on sensitivity, these three parameters are regarded as a constant C. Thus, Eq. (8) can be simplified as

$$S_\mathrm{min}=C\frac{K}{A_\mathrm{e}}. \tag{9}$$

where A_e is the effective area and K is Boltzmann' s constant.

3 MEGWO-PSO Algorithm Design and Implementation

For the layout-optimization problem of sparse planar antenna arrays in the field of radio astronomy, which has a broad search space and prominent multimodal characteristics, and for the challenge that traditional metaheuristic algorithms easily fall into local optima, this paper proposes a multi-strategy enhanced grey wolf–particle swarm (MEGWO-PSO) hybrid optimization algorithm. This algorithm divides global exploration and local development into two consecutive stages, as shown in Fig. 4, and incorporates multiple adaptive and enhancement mechanisms on this basis.

MEGWO-PSO Algorithm → Phase 1: Global search. The multi-dimensional enhanced GWO algorithm was used to quickly converge to the global optimum → "Warm start" transfer → Phase 2: Local development. The results of the first stage were used as the initial population, and the improved PSO algorithm was used for accurate optimization → Output the optimal solution.

图 4 MEGWO-PSO 分阶段步骤

Fig. 4 The phased steps of MEGWO-PSO

The main idea of the proposed algorithm can be summarized in the following three points:

1. **Two-stage collaborative framework:** The improved GWO and improved PSO algorithms are coordinated within a deeply coupled framework, effectively dividing the optimization process into two stages, namely global exploration and local exploitation. This avoids the limitations of a single algorithm and realizes the respective advantages of the algorithms through stage switching.

2. **Multi-strategy enhancement in the GWO stage:** In the first stage (global search stage), the MFGWO-PSO algorithm, on the basis of the standard GWO algorithm, first proposes a two-stage S-shaped attenuation convergence factor a, which is used to replace a_0 in the standard GWO. This convergence factor dynamically adjusts the search behavior in a nonlinear manner, enhancing the algorithm' s exploratory capability in the early search stage and its potential to jump out of local optima in the later stage. Meanwhile, drawing on the idea in GA of enhancing population diversity, adaptive crossover and mutation operations based on adaptive dynamic adjustment are integrated, maintaining population diversity and effectively suppressing premature convergence.

3. **Refined improvement in the PSO stage:** In the second stage (local exploitation stage), a "warm-start" mechanism is adopted, using the final optimization result of the first stage as the initial input of this stage, so that the subsequent local exploitation operation can be entered quickly, thereby greatly shortening the convergence time. In addition, to prevent

particles from falling into local optima during the local search stage, an adaptively decaying random disturbance term δ is added to the particle velocity update, further enhancing the particles' local optimization capability and ensuring the accuracy of the final solution.

The principles and procedures of each stage are described in detail below.

3.1 Improved Enhanced GWO Global Search Stage

3.1.1 Traditional GWO Search Scheme

The global search stage is the key to the optimization process of the algorithm, and its core task is to rapidly locate regions with high potential in a broad solution space. The traditional GWO algorithm divides the grey-wolf population into four classes: α, β, δ, and ω. Among them, α, β, and δ are the leaders of the population, guiding the behavior of the other grey wolves in the population (i.e., the evolutionary direction of the population); the ω wolves change their own position information according to the guidance of the leader wolves and continuously approach the prey position. Their update formulas are as follows:

$$\begin{cases} D_\alpha = |C_1 X_\alpha(t) - X(t)| \\ D_\beta = |C_2 X_\beta(t) - X(t)| \\ D_\delta = |C_3 X_\delta(t) - X(t)| \end{cases} . \qquad (10)$$

$$\begin{cases} X_1(t) = |X_\alpha(t) - A_1 D_\alpha| \\ X_2(t) = |X_\beta(t) - A_2 D_\beta| \\ X_3(t) = |X_\delta(t) - A_3 D_\delta| \end{cases} . \qquad (11)$$

$$X(t+1) = \frac{X_1(t) + X_2(t) + X_3(t)}{3}. \qquad (12)$$

In the above equations, C_i and A_i are coordination coefficients, $C_i = 2r_1$, $A_i = 2ar_2 - a$, and both r_1 and r_2 obey a uniform distribution on $[0, 1]$; D_α, D_β, and D_δ are respectively the distances between the current wolf to be updated and the three leader wolves α, β, and δ; $X_\alpha(t)$, $X_\beta(t)$, and $X_\delta(t)$ are respectively the positions of the three leader wolves α, β, and δ; $X(t)$ is the position of the wolf to be updated in the current generation; and $X(t+1)$ is the position of the wolf to be updated in the next generation.

In this optimization stage, the three types of leader wolves α, β, and δ in the grey-wolf algorithm correspond to the three best array distribution schemes screened out during the optimization process of the radio-astronomy antenna array; the implicit process in the algorithm whereby "the population approaches the prey" is essentially the process by which the array configuration converges toward the global optimal solution.

Although the traditional GWO algorithm has excellent global search capability, its linear attenuation mode of the convergence factor and lack of a diversity enhancement mechanism mean that, when facing the complex sparse antenna-array optimization problem in the field of radio astronomy, it still has the risk of premature convergence and falling into local optima. To solve these problems, this algorithm improves GWO as the first stage of the algorithm, mainly including the following two aspects.

3.1.2 Improved Two-Stage S-Shaped Attenuation Convergence Factor

In the GWO algorithm, the convergence factor is the core parameter balancing global exploration and local exploitation. In traditional GWO, the value of a_0 decreases linearly from 2 to 0, as shown in the following equation:

$$a_0 = 2 - \frac{2t_{\text{now}}}{t_{\max}}, \qquad (13)$$

where t_{now} and $t_{\max}$ are respectively the current generation and the total number of iterations. Its uniform attenuation rate may fail to meet complex optimization requirements in some cases. For example, in the early optimization stage, excessively rapid attenuation may cause the population' s exploratory capability to weaken rapidly; while in the later optimization stage, excessively slow attenuation may affect the precision of convergence.

Therefore, this paper proposes a two-stage S-shaped attenuation convergence factor $a(k)$. This factor controls the balance between exploration and exploitation through a nonlinear two-stage function, enabling the algorithm to exhibit more flexible search behavior at different stages. The mathematical model of this factor is as follows:

$$T_{\text{phase}} = \frac{k_{\max,\text{GWO}}}{2}. \qquad (14)$$

$$t_{\text{local}} = \begin{cases} k, & \text{if } k \le T_{\text{phase}} \\ k - T_{\text{phase}}, & \text{if } k > T_{\text{phase}} \end{cases}. \qquad (15)$$

$$a(k) = 2 \times \begin{cases} \frac{1}{2}\left\{1 + \left[\cos\left(\frac{t_{\text{local}} - 1}{T_{\text{phase}} - 1}\pi\right)\right]^{n_{\text{val}}}\right\}, \\ \qquad \text{if } t_{\text{local}} \le \frac{T_{\text{phase}}}{2}. \\ \frac{1}{2}\left[1 - \left|\cos\left(\frac{t_{\text{local}} - 1}{T_{\text{phase}} - 1}\pi\right)\right|^{n_{\text{val}}}\right], \\ \qquad \text{if } t_{\text{local}} > \frac{T_{\text{phase}}}{2}. \end{cases} \qquad (16)$$

Fig. 5 The variation curve of convergence factor $a(k)$

Figure 4: Fig. 5 The variation curve of convergence factor $a(k)$

where $k_{\text{max,GWO}}$ is the total number of iterations in the improved enhanced GWO stage, T_{phase} is the midpoint of the iteration period, and n_{val} is an adjustable parameter used to control the steepness of the curve. Its value is set within the range $[0.5, 1]$; in this paper, n_{val} is taken as 0.8.

When t_{local} lies within the first half of its half-period, its value slowly decays from 2 to 1, at which point the algorithm conducts wide-area search with relatively strong exploration intensity; when t_{local} lies in the second half of its half-period, its value rapidly decays from 1 to 0, at which point the exploitation capability of the algorithm is enhanced and it begins to carry out local fine search in the solution space. Suppose $k_{\text{max,GWO}} = 300$; the variation of $a(k)$ is shown in Fig. 5.

Fig. 5 The variation curve of convergence factor $a(k)$

From the variation curve of the convergence factor in the above figure, it can be seen that the two-stage S-shaped attenuation design using Eq. (16) endows the algorithm with stronger nonlinear search capability:

1. In the initial stage of iteration, through the slow attenuation characteristic of the front part of the cosine function and the amplification characteristic of the exponential function, it can be ensured that $|A_i| > 1$ for a relatively long time, thereby providing global search capability.
2. Then, in the middle of this stage, the convergence factor a can be restarted, allowing it to complete the same attenuation once again, thus avoiding the problem that the early stage falls into local optima without finding the approximate range of the optimal solution.
3. Finally, in the later stage, $|A_i| < 1$ is again maintained for a relatively long time, thereby finding a good approximate region of the optimal solution for the second stage of the algorithm.

3.1.3 Adaptive Crossover and Mutation Operations Integrated with the Genetic Algorithm

Although the improved convergence factor enhances the dynamic nature of GWO, the decrease in population diversity as the number of iterations increases remains an inherent challenge. To solve this problem, this algorithm uses the core crossover and mutation operations in the genetic algorithm as supplementary mechanisms for GWO position updating, and adaptively optimizes and improves these two operations.

1. Improved adaptive crossover operation

The purpose of the crossover operation is to exchange genes and integrate the excellent characteristics of different individuals, thereby generating offspring with greater competitiveness, namely array-element positions obtained by crossing different array distributions. This algorithm adopts an adaptive crossover strategy, in which the crossover probability P_c is no longer a fixed value, but is dynamically adjusted according to the fitness difference between the two individuals participating in crossover. The core design concept of this strategy is: the greater the fitness difference between individuals, the higher the crossover probability, thereby encouraging inferior individuals to absorb excellent genes from superior individuals and achieve rapid evolution. The calculation formula of P_c is as follows:

$$P_c = \begin{cases} P_{c0} \cdot \dfrac{\mathrm{fit}_{\mathrm{better}}}{\mathrm{fit}_{\mathrm{worse}}}, & \text{if } \mathrm{fit}_i \neq \mathrm{fit}_j, \\ P_{c0}, & \text{if } \mathrm{fit}_i = \mathrm{fit}_j. \end{cases} \tag{17}$$

where P_{c0} is the preset initial crossover probability; fit_i and fit_j are the fitness values of the paired individuals i and j, respectively; and $\mathrm{fit}_{\mathrm{better}}$ and $\mathrm{fit}_{\mathrm{worse}}$ are respectively the higher and lower fitness values among the paired individuals.

In addition, to avoid the possible destruction of the optimal solution caused by crossover operations, this algorithm introduces a key elite-protection mechanism. If one of the two individuals participating in crossover is the optimal solution (the α wolf), then this optimal solution will be strictly protected and will not participate in bidirectional crossover. Conversely, the other non-optimal individual will unidirectionally copy part of the excellent genes of the α wolf with a relatively low probability (for example, 30%), thereby realizing directional transmission of superior information while protecting the optimal solution.

2. Improved adaptive mutation operation

The purpose of the mutation operation is to introduce new randomness to prevent the algorithm from falling into a local optimum, while expanding the search range of solutions, that is, randomly changing the distribution of the antenna array. The adaptive mutation strategy designed in this algorithm has a mutation probability P_m that is related to the population convergence state and the individual

dynamic parameters related to the fitness value. Its design logic is based on real-time evaluation of population diversity.

First, the algorithm determines the population concentration by calculating the convergence ratio $R = \dfrac{\overline{\mathrm{fit}}}{\mathrm{fit}_{\mathrm{max}}}$, where $\overline{\mathrm{fit}}$ is the average fitness of the population and $\mathrm{fit}_{\mathrm{max}}$ is the best fitness of the current population. This ratio serves as an indicator for measuring population diversity, with the threshold $P_{\mathrm{m\_num}} = 0.8$.

(1) When the population tends toward convergence ($R \geq P_{\text{m\_num}}$): at this point, population diversity is insufficient, and the algorithm may have fallen into a local optimum. To enhance exploration capability, P_{m} will be significantly increased, and the calculation formula is:

$$P_{\text{m}} = P_{\text{m0}} \cdot \frac{\text{fit}_{\text{max}}}{\text{fit}_{\text{max}} - \text{fit}_{\text{min}}}. \qquad (18)$$

where P_{m0} is the initial mutation probability, and fit_{min} is the minimum fitness of the current population. This approach makes the mutation rate positively correlated with population concentration; when the solution set is highly concentrated (i.e., $\text{fit}_{\text{max}} - \text{fit}_{\text{min}}$ is small), P_{m} will increase significantly.

(2) When the population still has diversity ($R \leq P_{\text{m\_num}}$): the algorithm is in the normal exploration stage. The mutation probability P_{m} is negatively correlated with the fitness fit_k of the individual; individuals with lower fitness have higher mutation probabilities, encouraging them to conduct stronger exploration. The calculation formula is:

$$P_{\text{m}} = P_{\text{m0}} \cdot \frac{\text{fit}_{\text{max}} - \text{fit}_k}{\text{fit}_{\text{max}} - \overline{\text{fit}}}. \qquad (19)$$

This formula ensures that individuals with lower fitness (larger $\text{fit}_{\text{max}} - \text{fit}_k$) can obtain more mutation opportunities, while individuals with higher fitness tend to maintain their existing states, which is beneficial for local exploitation.

When the mutation operation is triggered, the selected gene position will be replaced by a new value generated completely at random. In this paper, the array element positions are stored in complex-number form, whose real and imaginary parts respectively represent offsets in two directions. The mutation process can be expressed as:

$$X_{\text{new}} = \text{rand} \cdot (X_{\text{sy}} - X_{\text{xy}}) + X_{\text{xy}} + \text{j} \cdot (\text{rand} \cdot (X_{\text{sz}} - X_{\text{xz}}) + X_{\text{xz}}), \qquad (20)$$

where X_{sy}, X_{xy}, X_{sz}, and X_{xz} are the boundary values of the search space. This strategy ensures that the mutation operation plays different roles at different stages of the algorithm: it provides diversity in the early stage of exploration, while in the later stage it serves as an effective means to escape local optima.

In summary, owing to the restart mechanism of the convergence factor and the existence of mutation and crossover operations, the possibility that the algorithm jumps out of local optima is enhanced, thereby accomplishing the task of global search very well. This stage takes the fitness function defined in Eq. (4) (the sum of the sidelobe levels in the azimuth and elevation cuts) as the optimization objective. Through the optimization-seeking behavior of the simulated gray wolf population, the transmitting antenna array gradually approaches the optimal arrangement range, and finally the optimization result of this stage is used as the input basis for local refinement in the second stage.

3.2 Improved PSO Local Exploitation Stage

After the first-stage optimization is completed, the improved GWO has converged to a high-quality solution set through global search. On this basis, the algorithm enters the second stage, namely the PSO local search stage. This stage will make full use of PSO' s efficient local fine-search capability to further optimize the solution set from the first stage; the optimization process still adopts the fitness function defined in Eq. (4), and the final goal is to obtain the transmitting antenna array layout scheme with the optimal fitness.

3.2.1 Population Initialization and "Warm Start" The particle swarm in the second stage is not initialized in the conventional random manner, but directly inherits the final population state of the GWO stage, specifically as follows:

(1) The final population of the improved enhanced GWO stage is used as the initial particle swarm of the PSO stage;

(2) The global optimal solution found by the improved enhanced GWO stage is taken as the swarm optimum of PSO (g_{best});

(3) Each individual in the improved enhanced GWO stage is taken as the personal optimum of PSO (p_{best}).

This "warm start" (Warm Start) strategy enables PSO to start from an already optimized starting point with good convergence, avoiding the time waste caused by re-random initialization, thereby greatly improving convergence speed and efficiency.

3.2.2 Particle Velocity Update with a Random Disturbance Term Introduced The standard PSO algorithm updates particle velocities through three components (the inertial term, the individual cognition term, and the social swarm term). However, in the later stage of optimization, when the particle swarm becomes overly concentrated, the values of these three terms tend toward zero, causing the particles to lose exploration capability and possibly fall into a local optimum.

To enhance the particles' escape ability in the local search stage, the MEGWO-PSO algorithm introduces an adaptive attenuating random disturbance term δ into the traditional PSO velocity update formula, with the value range $[0, 0.1]$. This disturbance term provides particles with a "microscopic" level of random exploration capability, thereby more effectively searching the neighborhood of the current optimal solution and avoiding potential local-optimum traps. To achieve the best balance between exploration and exploitation, the amplitude of the disturbance term decreases linearly with the number of iterations, and remains at in the second half of the PSO stage as

zero, to ensure final accurate convergence. δ^t is a random term that decays with time, and its update formula is:

$$\delta^t = \begin{cases} \epsilon \cdot \left(1 - \frac{k_{\mathrm{pso}}}{k_{\mathrm{max,PSO}}}\right), & \text{if } k_{\mathrm{pso}} < \frac{k_{\mathrm{max,PSO}}}{2}, \\ 0, & \text{if } k_{\mathrm{pso}} \geq \frac{k_{\mathrm{max,PSO}}}{2}, \end{cases} \tag{21}$$

where $\epsilon = 0.1$ is the initial maximum disturbance range; k_{pso} is the current number of iterations in the second stage; and $k_{\mathrm{max,PSO}}$ is the total number of iterations in the second stage.

Then the velocity formula for the updated particle i at the $t+1$-th iteration is:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_{\mathrm{best}}^t - x_i^t) + c_2 \cdot r_2 \cdot (g_{\mathrm{best}}^t - x_i^t) + \delta^t, \tag{22}$$

where v_i^t, p_{best}^t, and g_{best}^t respectively denote the velocity, individual optimum, and group optimum of particle i at the t-th iteration; w is the inertia weight, whose value decreases linearly with the number of iterations, so as to gradually reduce particle exploration in the local development stage; c_1 and c_2 are learning factors; r_1 and r_2 are random numbers in $[0, 1]$; δ^t provides an additional disturbance at the initial stage of optimization and gradually disappears in the later stage, thereby ensuring accurate convergence of the algorithm.

With the particle velocity obtained, the particle position update formula is:

$$x_i^{t+1} = x_i^t + v_i^{t+1}, \tag{23}$$

where x_i^{t+1} denotes the position of particle i at the $t+1$-th iteration. By updating particle velocity and position, the process of approaching the optimal array can be realized.

In summary, based on the fitness function defined above, the MEGWO-PSO algorithm, through a two-stage iterative mechanism of global search and local optimization, can efficiently converge to the optimal solution, providing a practical and effective technical scheme for sparse optimization of antenna arrays in the field of radio astronomy.

3.3 Algorithm Flow

The overall flow of this algorithm is shown in Figure 6, and its detailed steps can be summarized as the pseudocode shown in Figure 7.

4 Simulation and Analysis

4.1 Experiment 1: Sparse Optimization Analysis of a Small-Scale 100-Element Planar Array

Here, first, according to Figure 3, a model of a nonuniformly arranged planar array is established, with the array aperture being $L \times H$. The antenna array is set to lie in the *yoz* plane, with a total of Q antenna elements.

This experiment first verifies the effect of sparse optimization for a small-scale rectangular planar array. The array scale is the same as that used in the AGA (Adaptive Genetic Algorithms) algorithm proposed by Wu et al. (Ref. [24]), that is, the array aperture is $L = 10\lambda$, $H = 4\lambda$. The MEGWO-PSO algorithm designed in this paper is used to perform sparse placement. After sparsification, the number of array elements is $Q = 100$. The fitness calculation formula in Eq. (4) is adopted. After 300 iterations, the directional-pattern synthesis formula shown in Eq. (1) is used. The optimized array-element distribution diagram and the three-dimensional directional pattern of the array are shown in Figures 8 and 9, respectively.

To compare the specific merits of the algorithms, the GWO and PSO algorithms are separately applied to perform sparse placement under the same conditions. The comparison curves of the fitness evolution for the various algorithms are shown in Figure 10, and the fitness comparison is shown in Table 1.

The fitness of the array optimized by the MEGWO-PSO algorithm is 43.61 dB, which is better than those of the GWO and PSO algorithms in the comparison curves, and both ultimately converge. In addition, compared with the AGA algorithm in Ref. [24], whose fitness is 34.22 dB, the fitness value of the present algorithm is improved by 9.39 dB; compared with the SGA algorithm, whose fitness is 32.96 dB, it is improved by 10.65 dB.

The comparison directional patterns of the three algorithms, MEGWO-PSO, GWO, and PSO, in the azimuth and elevation cuts are shown in Figure 11.

The peak sidelobe levels of the three algorithms after optimization in the azimuth cut are shown in Table 2.

The comparison in Figure 11 and Table 2 shows that, among the three algorithms:

1. The MEGWO-PSO algorithm has the best suppression effect on sidelobe levels: in the directional pattern of the azimuth cut, the peak sidelobe level of the MEGWO-PSO algorithm is the lowest;
2. In the directional patterns of the elevation cut, because of the limitation imposed by the array aperture (elevation dimension) and the number of array elements, the optimization effects of the three algorithms are relatively close. This is not contradictory to the fact that the MEGWO-PSO algorithm has the best optimization effect.

Through Experiment 1, it is demonstrated that the MEGWO-PSO algorithm proposed in this paper can be well applied to small-scale ordinary rectangular planar arrays, and has a good optimization effect, outperforming the algorithms proposed in Ref. [24].

4.2 Experiment 2: Sparse Optimization Analysis of a Large-Scale 256-Element Planar Array

To verify that the algorithm proposed in this paper is not only applicable to Experiment 1' s

···for small-scale ordinary planar arrays of this type, but can also be applied to larger-scale radio-astronomy planar arrays. The array aperture used in this experiment is $L = 16\lambda$, $H = 16\lambda$, i.e., $16\lambda \times 16\lambda$. The key parameters in the field of radio astronomy considered are PSLL, half-power beam width (Half-Power Beam Width, HPBW), and sensitivity.

GA, PSO, GWO, and the MEGWO-PSO algorithm are respectively adopted. Under the same conditions, sparse optimization is performed for an array element configuration of 16×16, and the above related parameters are investigated and compared. The fitness calculation formula in Eq. (4) is used; Fig. 12 shows the evolution curve of the fitness function after 500 iterations.

Flowchart text in Fig. 6:

- Start
- Initialize the dimensions of the array, the upper and lower limits of the solution space, and the maximum number of iterations
- Initialize the gray Wolf population position
- The fitness value of each Wolf in the initial population is calculated, and the gray wolves with the top three fitness are found as the lead wolves, the positions are recorded and the positions of α, β, δ wolves are updated
- Update the position of other grey wolves (where double period S-shaped attenuation convergence factor is used)
- The improved bidirectional adaptive crossover operation is carried out for the gray Wolf population
- The grey Wolf population is improved by adaptive mutation operation
- Satisfying 60% of the maximum number of iterations?
  - no: return to the step of calculating the fitness value of each Wolf in the initial population
  - yes: proceed to the next stage
- The final population of the previous stage is used as the initial population for "warm start" and enter the local fine exploration stage
- The fitness value of each particle is calculated
- The optimal position and fitness value of individual particles are updated
- Update and replace the swarm optimal position and fitness value
- The random disturbance term is introduced to accelerate the local optimization ability

- Update the velocity formula and position of the particle
- Meet the maximum number of iterations?
  - no: return to "The fitness value of each particle is calculated"
  - yes: Output

图 6 MEGWO-PSO 算法的流程图

Fig. 6 The flowchart of the MEGWO-PSO algorithm

Algorithm 1 MEGWO-PSO for Sparse Array Optimization

Require: $k_{\max,\mathrm{GWO}}, k_{\max,\mathrm{PSO}}$, array params

Ensure: Optimal array f_{Best}

Phase I: Enhanced GWO

Initialize Positions

for $k = 1$ to $k_{\max,\mathrm{GWO}}$ **do**

  $a(k) \leftarrow \mathrm{DualCycle}(k)$

  Evaluate fitness, update α, β, δ

  $\mathrm{Positions}_i \leftarrow \frac{1}{3}\sum(\mathrm{leaders})$

  Adaptive crossover: $P_c = f\left(P_{c0}, \frac{\mathrm{fit}_{\mathrm{better}}}{\mathrm{fit}_{\mathrm{worse}}}\right)$

  Elite transfer: Positions $\leftarrow \alpha$

  Adaptive mutation: $P_m = f\left(P_{m0}, \frac{\mathrm{fit}_{\max}}{\mathrm{fit}_{\min}}\right)$

end for

Phase II: Enhanced PSO

ParticlePos $\leftarrow$ Positions, $g_{\mathrm{best}} \leftarrow \alpha$

for $k = 1$ to $k_{\max,\mathrm{PSO}}$ **do**

  $\delta^t \leftarrow e \cdot \left(1 - \frac{k_{\mathrm{PSO}}}{k_{\max,\mathrm{PSO}}}\right)$

  for each particle **do**

    $v_i^{t+1} \leftarrow w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_{\mathrm{best}}^t - x_i^t) + c_2 \cdot r_2 \cdot (g_{\mathrm{best}}^t - x_i^t) + \delta^t$

    $x_i^{t+1} \leftarrow x_i^t + v_i^{t+1}$

    Update $p_{\mathrm{best}}, g_{\mathrm{best}}$

  end for

end for

return f_{best} from g_{best}

Figure 7 Pseudocode of the MEGWO-PSO algorithm

Figure 8: The optimized array element distribution

Figure 5: Figure 8: The optimized array element distribution

Figure 9: The optimized 3D orientation map

Figure 6: Figure 9: The optimized 3D orientation map

Fig. 7 The pseudocode of the MEGWO-PSO algorithm

It can be seen from the above figure that, compared with the other three algorithms, the MEGWO-PSO algorithm proposed in this paper can find a very good optimal value. It fully utilizes the respective advantages of these three algorithms, not only ensuring a large-range local search in the early stage, but also ensuring rapid local convergence in the later stage, and ultimately finds an optimal solution superior to those of the other three algorithms.

Figure 8 Optimized array element distribution

Fig. 8 The optimized array element distribution

Figure 9 Optimized three-dimensional pattern

Fig. 9 The optimized 3D orientation map

The MEGWO-PSO algorithm is used to perform sparse array layout, and the resulting array' s azimuth-plane pattern, elevation-plane pattern, and three-dimensional pattern ⋯

The diagram and element distribution are shown in Fig. 13. The directional pattern is shown in Fig. 13, where the uniform array has 16×16 elements, with the elements arranged at a spacing of $d = \frac{\lambda}{2}$. After optimization by the present algorithm, the sparse array has a more prominent main lobe and the PSLL is also well suppressed. The comparison of the optimized PSLL in the azimuth section and pitch section is shown in Table 3. Compared with the uniform array, after optimization by the MEGWO-PSO algorithm, the PSLL is reduced by 15.25 dB and 15.34 dB, respectively.

Fig. 10 The fitness comparison curves

In Fig. 13, panels (a) and (b) are respectively the comparisons of the results optimized by the present algorithm with the uniform array in the azimuth and pitch sections.

Table 1 Comparison table of fitness after optimization by various algorithms

	MEGWO-PSO	GWO	PSO	AGA[1]	SGA[2]
Optimal value of fitness/dB	43.61	39.06	31.29	34.22	32.96

[1] Reference [24].

Fig. 11 The comparison of directional images of three algorithms, panel (a): comparison of azimuth section, panel (b): comparison of pitch section.

Table 2 Comparison table of optimization effect of three algorithms in azimuth section

	MEGWO-PSO	GWO	PSO
The optimized PSLL/dB	−30.57	−26.42	−18.99

To further analyze the specific optimization effect of the MEGWO-PSO algorithm on the directional patterns corresponding to the azimuth section ($\theta = \theta_0$) and the pitch section ($\varphi = \varphi_0$), under the same conditions, the comparative directional patterns of the arrays optimized by the four algorithms GA, PSO, GWO, and MEGWO-PSO in these two directions are plotted, and the results are shown in Fig. 14. In Fig. 14, panels (a) and (c) are the planar directional patterns of these four algorithms in the azimuth section and pitch section, respectively; panels (b) and (d) are their enlarged negative half-axis views, respectively. Table 4 shows the PSLL after optimization by each algorithm.

The experimental results show that the MEGWO-PSO algorithm proposed in this paper, when using the fitness function defined by Eq. (4) in Section 2 for sparse

After optimization, its PSLL values are lower than those of the three algorithms GA, PSO, and GWO, indicating the best optimization performance. The MEGWO-PSO algorithm achieves good suppression of the PSLL in both the azimuth cut and the pitch cut, while also taking both directions into account during optimization. Overall, in both directions, the MEGWO-PSO algorithm delivers better optimization results than the other three algorithms, and the maximum sidelobe level is lower than that obtained by the other three algorithms.

In the field of radio-astronomy, in addition to requiring a relatively low PSLL, there are also special requirements for other parameters, such as main-lobe width and antenna-array sensitivity. Next, the above parameters of the optimized arrays obtained by the four algorithms are calculated separately to further analyze the overall optimization performance of the MEGWO-PSO algorithm. The sensitivity is calculated using Eq. (9), and the various parameters are recorded as shown in Table 5.

Fig. 12 The comparison curves of fitness of the four algorithms

Fig. 13 The effect of MEGWO-PSO sparse distribution optimization, panel (a): azimuth section orientation, panel (b): pitch section orientation, panel (c): optimized 3D orientation, panel (d): optimized array element distribution.

[2] Reference [24].

Fig. 14 Comparison of the optimized directional maps by the four algorithms, panel (a): comparison of azimuth section, panel (b): enlargement of azimuth section, panel (c): comparison of pitch section, panel (d): enlargement of pitch section.

Figure 7: Fig. 14 Comparison of the optimized directional maps by the four algorithms, panel (a): comparison of azimuth section, panel (b): enlargement of azimuth section, panel (c): comparison of pitch section, panel (d): enlargement of pitch section.

Table 3 Situation of peak sidelobe levels after MEGWO-PSO optimization

	PSLL of azimuth section/dB	PSLL of pitch section/dB
MEGWO-PSO	−28.55	−28.64
Uniform array	−13.30	−13.30

From the data in the above table, it can be concluded that the optimal fitness value after optimization by the MEGWO-PSO algorithm is 57.19 dB, thereby proving that this algorithm is superior to the other three algorithms in terms of optimization search and rapid convergence. After MEGWO-PSO optimization, the PSLL values in the two directions are −28.55 dB and −28.64 dB, respectively; the suppression effect is the best, and the angles at which the PSLL occurs are also relatively late. In terms of the main-lobe width, the values of the MEGWO-PSO algorithm in the azimuth-section and pitch-section cuts are 3.82° and 3.83°, respectively. These values are very close to those of GA, PSO, and GWO, and are not broadened much; therefore, their influence on the main-lobe beam can be neglected. In terms of sensitivity, the sensitivity value of the array optimized by the MEGWO-PSO algorithm is 45.53C′Jy, while the sensitivity values of the other three algorithms are all inferior to that of the algorithm in this paper, indicating that the optimized sensitivity performance of the proposed algorithm is the best.

Fig. 14 Comparison of the optimized directional maps by the four algorithms, panel (a): comparison of azimuth section, panel (b): enlargement of azimuth section, panel (c): comparison of pitch section, panel (d): enlargement of pitch section.

In summary, the MEGWO-PSO algorithm can not only achieve good suppression of the PSLL in both directions, but also provide relatively good sensitivity. This also demonstrates from multiple perspectives the good optimization effect of the proposed algorithm in the field of astronomical radio.

Table 4 The situation of the peak sidelobe level after the optimization of the four algorithms

Algorithm	PSLL of azimuth section/dB	PSLL of pitch section/dB
GA	−26.11	−16.44
PSO	−17.88	−17.99
GWO	−24.94	−19.03
MEGWO-PSO	−28.55	−28.64

4.3 Experiment 3: Analysis of Antenna Array Patterns under Different Scanning Angles

On the basis of Experiment 1 and Experiment 2, we have obtained the optimal sparse array layout under specific conditions by using the MEGWO-PSO algorithm. To further verify the adaptability of this optimization result to wide-sky-area observation scenarios for radio astronomy, this part of the experiment focuses on analyzing the array pattern performance when the main-lobe beam pointing direction (i.e., the scanning angle) changes.

Continuing the core parameter configuration of Experiment 2: the same array aperture and number of sparse array elements are adopted. Based on the planar array layout obtained by the optimization in Experiment 2, performance verification is carried out by changing the scanning angle. It should be noted that all simulation analyses in Experiment 2 are based on the condition that the scanning angle is $(\theta_0, \phi_0) = (0^\circ, 0^\circ)$, and the corresponding array patterns were plotted after optimization. Now the scanning angle is adjusted to $(\theta_0, \phi_0) = (30^\circ, 45^\circ)$, and the characteristics of the array pattern under this scanning angle are analyzed. Fig. 15 gives the three-dimensional pattern of the uniform array under this scanning-angle condition.

Table 5 Record table of various parameters optimized by the four algorithms (Note: the "C" in the "sensitivity" column refers to the constant calculated using Eq. (9))

Section	Parameter	GA	PSO	GWO	MEGWO-PSO
	Optimal value of fitness/dB	42.55	35.87	43.97	57.19
Azimuth section	The Angle at the maximum sidelobe level/°	−9.28	−4.76	−15.29	−44.87
Azimuth section	PSLL/dB	−26.11	−17.88	−24.94	−28.55

Fig. 15 The 3D orientation map of uniform array at $(30^\circ, 45^\circ)$ scanning angle

Figure 8: Fig. 15 The 3D orientation map of uniform array at $(30^\circ, 45^\circ)$ scanning angle

Section	Parameter	GA	PSO	GWO	MEGWO-PSO
Azimuth section	HPBW/°	3.91	3.11	3.67	3.82
Pitch section	The Angle at the maximum sidelobe level/°	−8.77	−4.76	−6.27	−23.31
Pitch section	PSLL/dB	−16.44	−17.99	−19.03	−28.64
Pitch section	HPBW/°	3.23	3.10	3.96	3.83
	Sensitivity / Jy	61.22C	60.54C	50.60C	45.53C

Fig. 15 The 3D orientation map of uniform array at $(30^\circ, 45^\circ)$ scanning angle

Because the scanning angle has been changed, the sidelobe level of the uniform array at this time also increases; this makes it even more necessary to use a sparse array to suppress the increase in sidelobe level. Using the MEGWO-PSO algorithm to carry out sparse layout of the antenna array, the three-dimensional pattern of the optimized array under this scanning angle is shown in Fig. 16. Next, according to the beam synthesis formula, the array optimized by the proposed algorithm, the array optimized by the GWO algorithm with the best optimization effect among the other three algorithms (GA, PSO, GWO), and the uniform array are plotted for comparison in the azimuth and pitch sections under this scanning-angle condition, as shown in Fig. 17. The PSLL comparison of these three cases is shown in Table 6. It can be seen that, even when the scanning angle changes, the algorithm proposed in this paper can still effectively reduce the peak sidelobe level after optimization, and its effect is better than that of the GWO algorithm.

Fig. 16 The 3D directional map of the optimized array at $(30^\circ, 45^\circ)$ scanning angle

Next, fixing the scanning angle $\phi_0 = 0$, the range of the scanning angle θ_0 is further expanded to observe the optimization effect of the MEGWO-PSO

Fig. 16 The 3D directional map of the optimized array at $(30^{\circ}, 45^{\circ})$ scanning angle

Figure 9: Fig. 16 The 3D directional map of the optimized array at $(30^{\circ}, 45^{\circ})$ scanning angle

Fig. 17 Situation of antenna array pattern after optimization, panel (a): azimuth section comparison, panel (b): pitch section comparison.

Figure 10: Fig. 17 Situation of antenna array pattern after optimization, panel (a): azimuth section comparison, panel (b): pitch section comparison.

algorithm. When the scanning angle $(\theta_0, \phi_0) = (80^{\circ}, 0^{\circ})$, the pitch-section directional patterns of the uniform array, GWO, and MEGWO-PSO optimized arrays are plotted respectively, as shown in Fig. 18.

For the uniform array, when the main beam points to 80°, it can be clearly observed that an obvious grating lobe appears in the -80° direction. This grating lobe causes serious interference with the main lobe, and at the same time a relatively strong sidelobe level is also present near the main lobe. In comparison, the sparse array optimized based on the MEGWO-PSO algorithm can effectively suppress the grating-lobe effect at the same scanning angle; no grating lobe affecting the main-lobe performance appears in the -80° direction. Meanwhile, the array after sparse optimization reduces the PSLL, and its sidelobe suppression effect is superior to that of the GWO algorithm.

The above lists two special scanning-angle combinations. To verify the overall optimization performance of the MEGWO-PSO algorithm under different scanning-angle changes, the scanning angle is now gradually increased from $(0^{\circ}, 0^{\circ})$, and the comparative PSLL values under each group of scanning angles are recorded, as shown in Table 7.

Fig. 17 Situation of antenna array pattern after optimization, panel (a): azimuth section comparison, panel (b): pitch section comparison.

Table 6 Situation of peak sidelobe levels at $(30^{\circ}, 45^{\circ})$ scanning angles after MEGWO-PSO optimization

	PSLL of azimuth section/dB	PSLL of pitch section/dB
MEGWO-PSO	−20.01	−19.00
GWO	−16.90	−18.87
Uniform array	−13.16	−16.16

In summary, the MEGWO-PSO algorithm exhibits excellent sidelobe-suppression performance in array-pattern optimization, especially under different scanning angles. Its specific advantages can be reflected in the following two aspects. On the one hand, in the non-scanning scenario (i.e., when the scanning angle is ⋯

Under $(0^\circ, 0^\circ)$, this algorithm can already achieve strong suppression of the PSLL, effectively reducing the interference of the grating lobes in the array signal on the main-lobe signal and improving the accuracy of signal reception. On the other hand, even when the scanning angle changes, this algorithm can still maintain its grating-lobe suppression effect. Under different scanning-angle conditions, the total PSLL suppression in the two directions is significantly improved compared with that of the conventional uniform array and the array optimized by GWO. Among them, the minimum suppression amplitudes can reach 8.8 dB (relative to the uniform array) and 2.17 dB (relative to the GWO-optimized array), respectively; the maximum suppression amplitudes can reach 34.79 dB (relative to the uniform array) and 15.63 dB (relative to the GWO-optimized array), respectively. This fully demonstrates the stability and superiority of the proposed algorithm in scenarios with dynamically varying scanning angles.

In addition, the sparse array optimized by this algorithm can suppress the grating-lobe effect that readily appears in a uniform array under wide-angle scanning, making the main-lobe energy more concentrated and significantly improving the signal-reception accuracy during wide-angle scanning. This characteristic makes the sparse array optimized by the proposed algorithm more suitable for radio-astronomical observation under wideband scanning conditions, and enables it to serve related application scenarios more efficiently.

Fig. 18 The comparative directional map at $(80^\circ, 0^\circ)$ scanning angle

Table 7 The PSLL values of the array optimized by the MEGWO-PSO algorithm at different scanning angles

Scanning Angle	Uniform array: PSLL of azimuth section/dB	Uniform array: PSLL of pitch section/dB	GWO optimization: PSLL of azimuth section/dB	GWO optimization: PSLL of pitch section/dB	MEGWO-PSO optimization: PSLL of azimuth section/dB	MEGWO-PSO optimization: PSLL of pitch section/dB
$(0^\circ, 0^\circ)$	-13.30	-13.30	-24.94	-19.03	-28.55	-28.64
$(15^\circ, 0^\circ)$	-13.14	-13.17	-25.62	-18.74	-28.72	-18.88
$(15^\circ, 15^\circ)$	-13.14	-13.21	-19.08	-19.25	-21.76	-20.64
$(30^\circ, 15^\circ)$	-13.14	-13.49	-19.11	-17.92	-21.54	-16.84
$(30^\circ, 30^\circ)$	-13.17	-14.89	-19.12	-17.21	-21.16	-17.47
$(45^\circ, 30^\circ)$	-13.37	-18.86	-19.52	-13.78	-25.54	-21.02
$(45^\circ, 45^\circ)$	-13.35	-17.81	-19.10	-19.44	-21.28	-22.16
$(60^\circ, 45^\circ)$	-13.30	-17.24	-24.82	-17.98	-29.36	-18.11

Scanning Angle	Uniform array: PSLL of azimuth section/dB	Uniform array: PSLL of pitch section/dB	GWO optimization: PSLL of azimuth section/dB	GWO optimization: PSLL of pitch section/dB	MEGWO-PSO optimization: PSLL of azimuth section/dB	MEGWO-PSO optimization: PSLL of pitch section/dB
$(60^\circ, 60^\circ)$	-14.05	-16.39	-25.53	-17.65	-29.58	-18.05
$(75^\circ, 60^\circ)$	-14.02	-4.25	-25.23	-16.93	-28.74	-19.20
$(75^\circ, 75^\circ)$	-13.21	-4.34	-26.29	-17.33	-28.73	-18.74
$(80^\circ, 75^\circ)$	-13.14	0	-24.98	-15.59	-28.75	-18.24
$(80^\circ, 80^\circ)$	-13.14	0	-24.89	-15.71	-29.69	-17.65

5 Conclusion and Outlook

Aiming at the challenges faced in the optimization of low-frequency antenna arrays in radio astronomy, this paper proposes a multi-strategy enhanced hybrid Grey Wolf Optimizer–Particle Swarm Optimization (MEGWO-PSO) algorithm and successfully applies it to the layout optimization of sparse planar arrays. The algorithm integrates the global search capability of Grey Wolf Optimization (GWO) with the local fine-search advantage of Particle Swarm Optimization (PSO), constructing a two-stage collaborative optimization framework of global search and local search. By introducing a two-stage S-shaped attenuation convergence factor $a(k)$ together with adaptive crossover and mutation operations, the population diversity of the algorithm in the global search stage is enhanced, effectively preventing it from falling into local optima. Subsequently, through a "warm start" mechanism, the global solution from the first stage is used as the initial input for the second-stage PSO, and combined with an adaptively attenuated random disturbance term, significantly improving the convergence speed and solution accuracy of the algorithm.

The above content mainly focuses on the effectiveness and superiority of the MEGWO-PSO algorithm in array optimization. Through three sets of comparative simulation experiments, the following conclusions are obtained:

1. In the optimization of small-scale planar arrays, the MEGWO-PSO algorithm shows a significant advantage in PSLL suppression. Its optimization result is improved by 9.39 dB compared with Ref. [24], and it is clearly superior to independent PSO and GWO algorithms;

2. In large-scale array optimization tasks, for the core performance indicators in radio astronomy (PSLL and sensitivity), the MEGWO-PSO algorithm greatly improves the optimization effect: compared with the classical GWO, PSO, and GA algorithms, PSLL is reduced by 13.22 dB, 21.32 dB, and 14.64 dB, respectively, while sensitivity is improved by 10%, 24.8%,

and 25.6%, respectively;

3. In multi-azimuth scanning verification, the sparse array optimized by the MEGWO-PSO algorithm can maintain a lower PSLL value at different scanning angles, which can solve the problem of increased sidelobe levels during large-angle scanning and ensure stable array performance over a wide scanning range.

In summary, the MEGWO-PSO algorithm proposed in this paper performs excellently on multiple key performance indicators of sparse planar arrays, including PSLL, sensitivity, and scanable region, providing a more competitive technical solution for low-frequency radio astronomical observations. Future research will focus on analyzing the optimization capability under broadband and multi-frequency-point conditions, and further explore its application in multi-objective optimization problems, such as simultaneous optimization of PSLL and array gain.

References

[1] Liu Hui, Wang Xinkuan, Wen Qian, et al. Modern Radar, 2025, 10: 1

[2] Di Serio A, Adolfo. ITAP, 2020, 68: 4604

[3] Fang Shuxiang, Li Weiming, Xue Zhenghui, et al. Journal of Microwaves, 2020, 36: 7

[4] Liu Shengwen, Wang Chao. Computer Measurement & Control, 2023, 31: 246

[5] Dong Liang, Zhang Ming, Xie Huanhuan, et al. Astronomical Research & Technology, 2023, 20: 421

[6] Mailloux R J. Phased Array Antenna Handbook: 2nd ed. Translated by Nanjing Electronic Technology Research Institute. Beijing: Publishing House of Electronics Industry, 2007: 25–29

[7] Lao Baoqiang, An Tao, Chen Xiao, et al. Acta Astronomica Sinica, 2017, 58: 110

[8] Nijboer J, Pommier P M, Bruy G A, et al. LOFAR Imaging Capabilities and System Sensitivity. SKA Memo 113, 2009

[9] Wu Yang, Du Biao, Jin Chengjin, et al. Chinese Journal of Radio Science, 2016, 31: 413

[10] An Tao, Wu Xiangping, Hong Xiaoyu, et al. Bulletin of the Chinese Academy of Sciences, 2018, 33: 871

[11] Guo Shaoguang, An Tao, Xu Zhijun, et al. Scientia Sinica: Physica, Mechanica & Astronomica, 2023, 53: 6

[12] Huang Jian, Pei Naichang. Telecommunications Technology, 2022, 62: 17

[13] Bregman J B. A Wideband Sparse Fractal Array Antenna for Low Frequency Radio Astronomy. IEEE Antennas and Propagation Society International Symposium, Salt Lake City, UT, USA, July 16–21, 2000

[14] Braun R, van Cappellen W. 2006, arXiv: astro-ph/0611160

[15] de Lera Acedo E, Bolli P, Paonessa F. ExA, 2018, 45: 1

[16] Kogan L, Cohen A, Polisensky E. Elliptical LWA Station Configurations Optimized to Minimize Side Lobes. LWA Memo #139, 2008

[17] He Y Z, Wang C X. Electronics, 2023, 12: 1763

[18] Li Runze, Zhang Haiting, Cai Xiujin. Computer Measurement & Control, 2025, 33: 175

[19] Di J, Dong L, He W. ATI, 2025, 2: 100

[20] Dutta K P, Mahanti G K. International Journal of Communication Systems, 2024, 37: 5760

[21] Allawi Z T. Processes, 2019, 7: 657

[22] Katoch S. Multimedia Tools and Applications, 2021, 80: 8091

[23] Yan M. IMWTL, 2025, 25: 81

[24] Wu Z H. An Improved Optimization for Constrained Sparse Planar Arrays Based on Adaptive Genetic Algorithm. 2024 IEEE 12th Asia-Pacific Conference on Antennas and Propagation, Nanjing, September 22–25, 2024

[25] Liu Xiaozhong, Yang Wansheng, Gao Zhaozhao. Journal of Microwaves, 2011, 27: 32

[26] Yu H N. EneE, 2024, 121: 6

[27] Liu Y Y. NCAA, 2024, 36: 2713

[28] Tao Kui, Wang Bin, Tian Xue, et al. Chinese Journal of Radio Science, 2024, 39: 492

[29] Mirjalili S, Mirjalili S M. Advances In Engineering Software, 2014, 46: 61

[30] Amiriebrahimabadi M, Mansouri N. Multimedia Tools and Applications, 2024, 83: 47775

[31] Hu Jingjie, Chu Zhaobi, Guo Yuele, et al. Computer Applications and Software, 2023, 40: 2068

[32] Sachan S. *International Journal of System Assurance Engineering and Management*, 2025, 16: 3325

[33] Men Maotan, Zhao Rui, Zhang Jinshuai, et al. *Journal of Zhejiang University (Engineering Science)*, 2024, 58: 1255

[34] He Jie, Feng Dazheng, Li Xiaoming. *Journal of Microwaves*, 2010, 26: 55

[35] Ellingson S W. *ITAP*, 2011, 59: 1855

Application and Analysis of Multi-Strategy Enhanced Grey Wolf Particle Swarm Algorithm in Radio Array Optimization

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Abstract The Peak Side Lobe Level (PSLL), sensitivity, and directivity of a radio antenna array directly determine the performance of a system in weak signal detection, anti-interference, and resolution capabilities. In applications spanning the High Frequency (HF) to Very High Frequency (VHF) bands, uniform arrays suffer from high sidelobes and grating lobes during wide-angle scanning, while traditional sparse array optimization algorithms are prone to premature convergence and local optima trapping. To address these issues, this study proposes a Multi-strategies Enhanced Grey Wolf Optimization-Particle Swarm Optimization (MEGWO-PSO) algorithm for the sparse layout optimization of two-dimensional planar arrays. The algorithm adopts a two-stage framework of global exploration and local refinement. In the first stage, an enhanced grey wolf algorithm integrated with a double-order S-shaped attenuation convergence factor, along with adaptive crossover and mutation operators, is employed to achieve efficient global search and avert premature convergence. In the second stage, the optimized search space derived from the first stage is used as the initial input, and local refinement is performed via an improved particle swarm optimization algorithm. Simulation results demonstrate that MEGWO-PSO can effectively optimize the layout of small-to-medium-sized arrays with up to 100 elements, reducing the PSLL by 9.39 dB compared with the results reported in relevant literature. For large-scale 256-element arrays, considering the key performance metrics of radio antenna arrays, the proposed method yields a PSLL that is 13.22 dB, 21.32 dB, and 14.64 dB lower than those of the standalone GWO, PSO, and GA (Genetic Algorithm) algorithms, respectively. Meanwhile, the array' s sensitivity is enhanced by 10%, 24.8%, and 25.6% relative to the three aforementioned algorithms. Furthermore, the optimized array exhibits superior PSLL suppression across different scanning angles, with reductions of 34.79 dB and 15.63 dB compared with uniform arrays and GWO-based sparse arrays, respectively. This work provides a viable technical approach and theoretical support for the development of radio telescopes with large apertures, high performance, and wide-angle scanning capabilities.

Key words methods: multi-strategies enhanced grey wolf optimization-particle swarm optimization (MEGWO-PSO) algorithm, instrumentation: sparse array, sensitivity, techniques: peak side lobe level (PSLL), techniques: wide angle scanning

Note: Figure translations are in progress. See original paper for figures.