

Particle Swarm Optimization Algorithm for Visible Light Transmission Performance

Jialing Ge *

School of Physics and Electronic Information Engineering, Zhejiang Normal University, Jinhua, 321019, China

* Corresponding Author Email: Jaelin@zjnu.edu.cn

Abstract. With the development of precision imaging, micro-nano optics, and intelligent manufacturing, complex optical systems are placing higher demands on image quality, cost, and manufacturability. Traditional design processes based on damped least squares and algorithms such as genetics and differential evolution are becoming increasingly inadequate in terms of global optimization and automation. This paper focuses on the application of particle swarm optimization (PSO) in optical model optimization. It uses a combination of literature review and comparative analysis to summarize the research progress of PSO in lens design, freeform and aspherical surface optimization, optical thin films, and structural colors, as well as illumination and antenna optical systems in the past five years. Starting with standard PSO, adaptive PSO, multi-objective PSO, and hybrid frameworks such as PSO + local optimization and PSO + intelligent algorithm. This paper summarizes their advantages in search efficiency, solution diversity, and design automation, and analyzes problems such as premature convergence, high computational cost, parameter sensitivity, and insufficient embedding of physical constraints. Finally, it proposes development directions such as physical information-driven approaches, surrogate model acceleration, and multi-algorithm hybrid optimization, providing a reference for the research and engineering application of optical intelligent design methods.

Keywords: Particle swarm optimization, optical model optimization, intelligent optimization, hybrid algorithm, physical information.

1. Introduction

In recent years, with the dramatic increase in the dimensions and constraints of complex optical systems such as precision imaging and lithography, traditional local optimization methods, represented by damped least squares, have gradually shown their inadequacy in terms of global optimization and automation. Zhang et al. proposed an extreme ultraviolet lithography source-mask optimization method based on the thick mask model and social learning particle swarm optimization (PSO) in Optics Express, which significantly reduced the imaging error of various target patterns and demonstrated the potential of PSO in high-dimensional optical imaging optimization [1].

This paper focuses on the application of particle swarm optimization (PSO) in typical optical models. Combining the review of PSO system overviews on algorithm variants and application trends, it summarizes and compares representative studies in optical phased arrays, uniform illumination of light source arrays, lithographic SMO, and mid-wave infrared zoom systems over the past five years. The aim is to summarize the advantages and limitations of PSO in global search and convergence compared with traditional methods in optical intelligent design, and to propose subsequent research directions for physical information-driven and hybrid optimization frameworks [2].

2. Particle Swarm Optimization Algorithm Principle

Particle swarm optimization is based on observations of bird flocks' foraging behavior: when birds are looking for food, they do not know the exact location of the food, but they can continuously adjust their flight direction based on two types of experience: "their current location" and "the bird among their companions that is closest to the food," and eventually find the food.

In the particle swarm optimization algorithm, each particle corresponds to a candidate solution to the optimization problem. Particles have two attributes in the solution space: "position" and "velocity". The fitness function is used to evaluate the quality of the current position. The motion of a particle is determined by two pieces of information. One is the best position encountered in one's own history, which is the individual extreme value 'pbest', and the other is the best position that has occurred in the history of the entire population, which is the population extreme value 'gbest'. By continuously updating the velocity and position of the particles, the entire particle swarm gradually converges towards the optimal solution region, thus completing the optimization search.

A swarm of particles is randomly generated in the feasible solution space, and each particle is denoted as

Position vector

$$X_i=(X_{i1},X_{i2},\dots,X_{iD})^T \quad (1)$$

velocity vector

$$V_i=(V_{i1},V_{i2},\dots,V_{iD})^T \quad (2)$$

Where $i=1,2,\dots,N$ is the particle number and D is the problem dimension.

For each particle, calculate its fitness value $f(X_i)$. The better the fitness, the better the solution corresponding to the particle. Record the individual best position 'pbest' that the particle has experienced so far, and the global best position 'gbest' of the entire particle swarm so far.

For the i - th particle, its individual extreme value position vector is denoted as

$$P_i = (P_{i1}, P_{i2}, \dots, P_{iD})^T \quad (3)$$

For the current population, its population extremum location vector is denoted as

$$P_g = (P_{g1}, P_{g2}, \dots, P_{gD})^T \quad (4)$$

Fitness is recalculated whenever a particle's position X_i changes. If the fitness of the new position is better than the individual best value in the particle's history, then the new position P_i is used. If the fitness of the new position is better than the population best value in the history of all particles, then the new position is used to replace P_g . This is its update rule.

In each iteration, the speed update formula from generation k to generation $k + 1$ is

$$V_{id}^{k+1} = w \cdot V_{id}^k + c_1 \cdot r_1 \cdot (P_{id}^k - X_{id}^k) + c_2 \cdot r_2 \cdot (P_{gd}^k - X_{id}^k) \quad (5)$$

Where, V_{id}^k represents the velocity component of the i -th particle in the i -th dimension at generation i ; X_{id}^k represents the position information of the i -th particle in the i -th dimension at generation j ; P_{id}^k represents the component of the individual optimal position of the i -th particle in the i -th dimension; P_{gd}^k represents the component of the population optimal position in the i -th dimension; w represents the inertia weight, which controls the inertia of the particle to maintain its original velocity; c_1, c_2 is the acceleration coefficient, the learning factor, which is a non-negative constant, corresponding to the intensity of individual learning and group learning, respectively; r_1, r_2 is a random number that follows a uniform distribution in the interval $[0,1]$, used to increase the randomness of the search.

In each iteration, the position update formula from generation k to generation $k + 1$ is

$$X_{id}^{k+1} = X_{id}^k \quad (6)$$

Fig. 1 shows the flowchart of the particle swarm optimization algorithm.

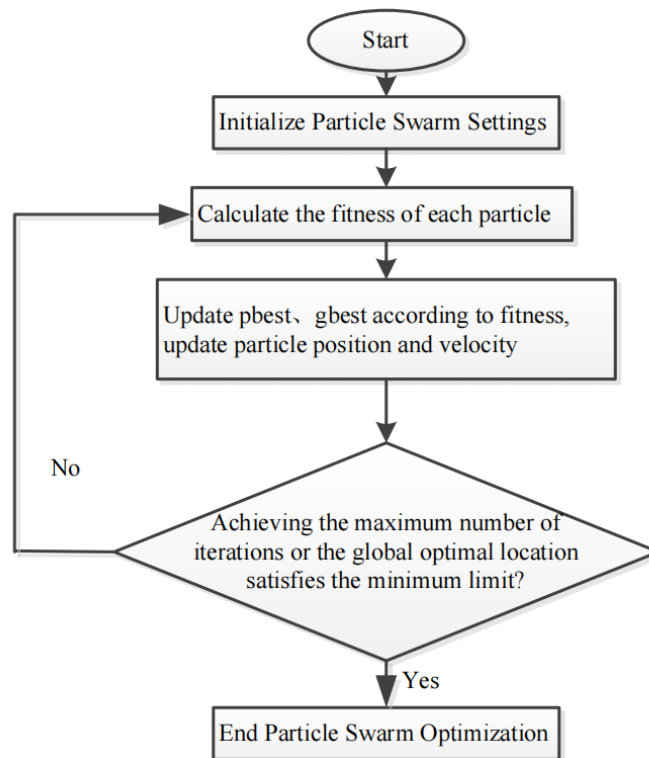


Fig 1. Algorithm Flowchart (Photo/Picture credit: Original).

3. Compare with Past Algorithms

In the field of optical model optimization, a variety of improved or hybrid frameworks based on particle swarm optimization have emerged in recent years. Their common feature is that they exhibit stronger global search capabilities and better performance with a cost trade-off in highly nonlinear, multi-peak, and multi-constraint design spaces compared to traditional numerical algorithms or other metaheuristic algorithms.

3.1. Global Optimization Advantages of Improved PSO in Non-Uniform OPA Design

Taking the design of non-uniform optical phased arrays as an example, Zang et al. performed a global search for the antenna spacing of a one-dimensional waveguide OPA based on multi-strategy enhanced PSO [3].

By introducing chaotic initialization, adaptive inertial weights, and dynamic learning factors, compared with the genetic algorithm and the traditional PSO algorithm, the multi-strategy enhanced PSO proposed in this paper can improve the peak sidelobe level of 32-channel and 64-channel arrays at 60° by about 2 dB within a large-angle scan range of $\pm 60^\circ$. Furthermore, the change in PSLL is less than 0.8 dB for both 32-channel and 64-channel arrays. Assuming that a larger antenna spacing has a slightly more significant impact than a smaller spacing, overall, it exhibits better scan robustness and global convergence behavior than the traditional optimization method that targets 0° PSLL. This demonstrates that under complex array structures and multiple operating conditions, the improved PSO can achieve a better solution in terms of suppressing gate lobes and taking into account array aperture and manufacturing constraints.

3.2. The Fast Convergence Advantage of TLVPSO in Uniform Illumination of Light Source Arrays

In the design of uniform illumination for light source arrays, Ma et al. proposed the Tent-Lévy Mutant Particle Swarm Optimization (TLVPSO) algorithm for laser diode arrays used for supplemental lighting of plants. By introducing Tent chaotic mapping, Lévy flight, nonlinear inertial

weights, and adaptive learning factors, the algorithm's global exploration capability and population diversity were significantly enhanced [4].

On the standard test function, TLVPSO outperforms various PSO variants (PSO, CFPSO, DFPSO, SAPSO, IDWPSO) in both optimal and average values. In actual laser array optimization, compared with these baseline algorithms, it reduces the convergence time by about 10–20% and maintains a more stable convergence trajectory under almost the same optimal illumination uniformity. This result demonstrates that for applications requiring frequent calls to optical simulation software to evaluate objective functions, the improved framework based on PSO can achieve more stable structural parameters that are closer to the global optimum while controlling computational costs.

3.3. The Combined Advantages of Precision and Efficiency of GA-APSO in Photolithography SMO

In terms of complex imaging systems, the GA-APSO hybrid algorithm proposed by Liu et al. combines the genetic algorithm (GA) with the adaptive PSO for lithography source-mask joint optimization (SMO), making full use of the global diversity maintenance of GA and the fast convergence characteristics of PSO [5].

Numerical experiments on simple symmetrical and complex patterns show that, compared with GA and APSO alone, the GA-APSO optimized photoresist pattern error is reduced by 40.13–52.94% and 10.28–33.31%, respectively, while the computation time is reduced by 75.91–87.00% and 48.43–58.66%, respectively, and the results of repeated calculations fluctuate less [5]. This demonstrates that in high-dimensional, highly nonlinear imaging quality optimization problems, the hybrid meta-heuristic framework based on PSO can achieve a trade-off between accuracy, efficiency, and result stability that is significantly better than that of a single algorithm.

3.4. The Adaptability Advantages of PSO in the Initial Structural Design of the MWIR Zoom System

In mid-wave infrared zoom optical systems, Zhenhao Liu et al. combined PSO with paraxial matrix optical analysis to solve the initial structural parameters of a large zoom ratio three-motion zoom lens [6].

The paper compares the shortcomings of the traditional PWC analytical method, the patent-based empirical method, and optimization methods based on genetic algorithm and simulated annealing, and points out that PSO has advantages such as fewer parameters, simple implementation, fast convergence speed in the early iteration stage, and strong adaptability to high-dimensional non-convex problems [6]. The automatic solution method based on PSO finally obtained a compact MWIR zoom system with a zoom ratio of 50×, a total system length of less than 530 mm, and a focal length/total length ratio of about 2:1, which verifies the feasibility and effectiveness of the method in a complex multi-solution space.

3.5. A Summary of Past Algorithm Research

The above work demonstrates that the advantages of particle swarm optimization (PSO) and its improvements in optical model optimization lie primarily in its ability to maintain strong global search capabilities in parameter spaces characterized by strong nonlinearity, multiple peaks, multiple constraints, and even a mixture of continuous and discrete parameters. This avoids the problem of traditional damped least squares or single heuristic algorithms easily getting trapped in local optima. Furthermore, PSO facilitates coupling with optical physical models and commercial simulation software, allowing direct optimization of physical indices (PSLL, image error, image quality, and structural dimensions) by invoking FDTD, lithography imaging models, or paraxial matrix analysis. Finally, by combining with algorithms such as GA or local optimization strategies, convergence speed and result stability can be further improved while maintaining high design freedom. Future optical intelligent design methods can build upon this foundation, continuing to expand along the lines of "improved PSO strategies + physical constraint embedding + multi-objective/multi-scenario unified

optimization," providing a more automated and interpretable optimization framework for complex optical systems.

4. Analysis

Although particle swarm optimization (PSO) has been widely used in optical model optimization and has shown significant advantages over traditional damped least squares, genetic algorithms, and differential evolution methods in terms of global search capability, design freedom, and coupling with commercial optical software, the work reviewed in this paper shows that existing PSO still has a series of shortcomings that restrict its further application.

First, under conditions of high noise, system instability, or limited population size, standard PSO is prone to premature convergence, causing the particle swarm to gather near the suboptimal solution too early [7]. To this end, Woo et al. introduced a dynamic mutation mechanism in optical wavefront shaping, which effectively improved the robustness of the algorithm in the experimental environment by adaptively increasing population diversity, indicating that it is necessary to design adaptive PSO variants for engineering scenarios in optical applications to address noise and disturbances [7].

Secondly, in the reverse design of structural colors and multilayer optical thin films, Wang and Guo pointed out that when material type and geometric parameters are used as optimization variables at the same time, relying solely on PSO to search directly on the full-wave simulation model will result in extremely high computational cost and poor scalability [8]. The NEUTRON framework they proposed approximates the "structure-spectral response" mapping by using a neural network surrogate model and then runs PSO in the surrogate space, achieving joint optimization of material and geometric parameters. This suggests that PSO should be combined more with machine learning and surrogate modeling in complex optical models in the future to alleviate the simulation cost bottleneck [8].

Furthermore, in large-scale optical systems with multiple targets and constraints, traditional "black box" PSOs often fail to fully utilize the physical structure of the problem, resulting in slow convergence speeds and a tendency to remain at suboptimal solutions. Jiang et al. proposed a Physical Auxiliary Particle Swarm Optimization (PA-PSO) algorithm in the design of Ka-band metal lens antennas. The algorithm embeds optical priors such as variational extreme conditions and rotational symmetry into the search space and update rules, which effectively narrows the feasible region and significantly improves the convergence efficiency [9]. This indicates that explicitly incorporating optical physical constraints into PSO is one of the key directions for improving algorithm efficiency and the physical plausibility of the solution.

In addition, Sheng et al. systematically analyzed the influence of different inertial weights and learning factors on the convergence behavior of PSO in the design of broadband achromatic metal lenses. They found that the algorithm's performance is highly sensitive to parameter settings and is prone to oscillation and stagnation under multi-peak targets. Therefore, they further coupled the improved PSO with the genetic algorithm and used the crossover and mutation mechanisms of GA to maintain population diversity, thus achieving better convergence speed and global optimization capability than single PSO [10].

Based on the above analysis, this paper argues that future particle swarm optimization for optical models can be advanced in four aspects.

First, it develops dynamic mutation and adaptive parameter adjustment strategies to enhance noise resistance and suppress premature convergence.

Simultaneously, a "physical prior + PSO" physically driven framework can be constructed, explicitly utilizing aberration theory, symmetry, and energy conservation principles during the search process.

Combining surrogate models such as neural networks with multi-objective optimization techniques can reduce the computational cost of complex optical simulations while simultaneously balancing image quality, efficiency, and cost. This is also a promising direction for development.

Finally, a hybrid optimization architecture combining PSO with algorithms such as GA and DE can be designed to leverage the complementarity of different algorithms in global exploration and local convergence, thereby further enhancing the engineering applicability of PSO in optical intelligent design based on previous research.

5. Conclusion

In summary, this paper systematically reviews and compares the application of particle swarm optimization in optical model optimization.

Compared to traditional damped least squares gradient-based local optimization methods and classical metaheuristic methods such as genetic algorithms and differential evolution, PSO demonstrates stronger global search capabilities, greater design freedom, and easier engineering integration with commercial optical software in typical optical problems with high parameter dimensionality, strong nonlinearity of objective functions, multi-peak, and continuous-discrete hybrid approaches. It has achieved significantly better optimization results than traditional methods in scenarios such as lens structure design, metallic lenses, optical phased arrays, and thin film/structured color.

However, existing work shows that PSO still has shortcomings such as premature convergence, high sensitivity to inertia weights and learning factors, high computational cost, and difficulty in explicitly handling complex physical constraints. Based on this, this paper suggests that future research should focus on improving the PSO-based optical intelligent design method along several paths. First, introduce strategies such as adaptive inertia weighting and dynamic mutation to enhance population diversity and noise resistance. Second, embed optical physics priors into the objective function and search space to develop a physics-assisted or physics-information-driven PSO framework. Third, combine surrogate models such as neural networks with multi-objective optimization techniques to reduce simulation costs while simultaneously considering image quality, efficiency, and cost. Fourth, form a hybrid optimization framework with genetic algorithms and differential evolution to comprehensively leverage the complementary advantages of different algorithms in global exploration and local convergence, thereby further improving the performance and engineering applicability of PSO-based optical intelligent design methods.

References

- [1] Zhang Z, Li S, Wang X, Cheng W, Qi Y. Source mask optimization for extreme-ultraviolet lithography based on thick mask model and social learning particle swarm optimization algorithm. *Optics Express*, 2021, 29(4): 5448–5465.
- [2] Gad A G. Particle swarm optimization algorithm and its applications: A systematic review. *Archives of Computational Methods in Engineering*, 2022.
- [3] Zang Z, Wu J, Huang Q. Design of an aperiodic optical phased array based on the multi-strategy enhanced particle swarm optimization algorithm. *Photonics*, 2025, 12(3): 210.
- [4] Ma Z, Lan Y, Chen X, Guo Y. Optimal design of laser diode arrays for uniform illumination using hybrid particle swarm optimization. *Applied Optics*, 2025, 64(23): 6681–6690.
- [5] Liu J, Zhou J, Sun H, Jin C, Wang J, Hu S. The inverse optimization of lithographic source and mask via GA-APSO hybrid algorithm. *Photonics*, 2023, 10(6): 638.
- [6] Liu Z, Zhang J, Huang Y, Zhang X, Wu H, Zhang J. Compact high-zoom-ratio mid-wavelength infrared zoom lens design based on particle swarm optimization. *Sensors*, 2025, 25(2): 467.
- [7] Woo C M, Li H, Zhao Q, Lai P. Dynamic mutation enhanced particle swarm optimization for optical wavefront shaping. *Optics Express*, 2021, 29(12): 18420–18426.
- [8] Wang H, Guo L J. NEUTRON: Neural particle swarm optimization for material-aware inverse design of structural color. *iScience*, 2022, 25(5): 104339.

- [9] Jiang S, Deng W, Wang Z, Cheng X, Tsai D P, Shi Y, Zhu W. Ka-band metalens antenna empowered by physics-assisted particle swarm optimization (PA-PSO) algorithm. *Opto-Electronic Science*, 2024, 3: 240014.
- [10] Sheng P, Hao R, Chen G, Wang W, Liu J, Xu J, Li H, Kong J, Zhao J. Broadband achromatic metalens design based on the combination of an improved particle swarm optimization algorithm and a genetic algorithm. *Applied Optics*, 2024, 63(36): 9176–9182.