Improved Zebra Optimization Algorithm with Multi-Strategy Fusion

Wenhan Luo, Pengliang Zhao

Abstract— **Although the Zebra Optimization Algorithm (ZOA) has the advantages of fewer parameters and easy implementation, its premature convergence and tendency to fall into local optima limit its practical applications. To address these issues, this paper proposes a multi-strategy improved Zebra Optimization Algorithm (IZOA). Firstly, a longitudinal-transverse crossover strategy is integrated to enable multi-dimensional information interaction within the population, enhancing global search capabilities in complex solution spaces. Secondly, a nonlinear dynamic scaling factor is designed to balance exploration and exploitation through an adaptive step-size adjustment mechanism. Additionally, a lens imaging reverse learning strategy is introduced to expand the search scope by generating reverse solutions based on optical imaging principles. Finally, 13 standard benchmark functions are utilized to comprehensively evaluate the improved IZOA, the original ZOA, the Whale Optimization Algorithm (WOA), and the Golden Jackal Optimization (GJO) algorithm. Experimental results demonstrate that IZOA outperforms the other three algorithms in terms of convergence speed and global search capability.**

Index Terms—**Zebra Optimization Algorithm (ZOA); Flexible Job Shop Scheduling (FJSP); Longitudinal-Transverse Crossover Strategy; Lens Imaging Reverse Learning; Dynamic Scaling Factor.**

I. INTRODUCTION

Faced with the dual pressures of a multi-variety small batch order model and cost efficiency, flexible job shop scheduling (FJSP) has become key to breaking through manufacturing efficiency bottlenecks. Its optimization can increase equipment utilization by 15%-30% and shorten cycles by more than 20%. However, traditional scheduling methods have limitations in handling dynamic constraints and global optimization, and existing intelligent algorithms (such as GA and PSO) also face challenges of premature convergence and insufficient adaptability to dynamics. This study innovatively proposes a hybrid zebra optimization algorithm (ZOA), constructing a new scheduling solution through the bionic intelligent behavior of zebra groups. The core breakthroughs include: (1) constructing a multi-dimensional constraint coding model and using an adaptive penalty function to achieve precise mapping of equipment flexibility and process sequence; (2) embedding a dynamic hierarchical strategy and a tabu search mechanism to enhance the algorithm's global search capability, effectively balancing exploration and exploitation; (3) integrating real-time production data and energy consumption indicators to establish a dual-objective optimization model for efficiency and sustainability, improving responsiveness to dynamic scenarios such as equipment failures and emergency orders. This algorithm expands the application boundary of bionic optimization algorithms at a theoretical level and can be integrated into digital twin systems in practice, providing dynamic scheduling support for smart factories, with universality for transition to complex manufacturing scenarios such as semiconductors and aerospace. The research overcomes pain points such as resource mismatches and delayed responses in traditional scheduling through an interdisciplinary approach, providing a technical pathway for the intelligent upgrading of the manufacturing industry that is both innovative and practical, aiding in the coordinated development of improved production efficiency and green transformation.

II. RELATED WORK

With the continuous development of the times, the demands of society for productivity are also constantly rising, and workshop scheduling has become a research hotspot. In literature [6], Yin Jianjin, Zhang Beike, and others proposed an improved continuous bat algorithm to solve the flexible flow shop scheduling problem. Since the bat algorithm has rarely been applied to discrete fields since its introduction, this paper maintains the use of continuous values to represent machine numbers while proposing a coding strategy that fixes processes and encodes machines. Additionally, an adaptive factor is introduced in the algorithm's position update to enhance the search ability and convergence of the algorithm. In literature [7], Yao Yuanyuan and Ye Chunming proposed applying an improved gray wolf algorithm to job shop scheduling. The first step introduces dynamic operations in the population to eliminate poor individuals; a reverse learning strategy is added during population initialization to enhance diversity, which helps improve the algorithm's global search ability and yields higher quality solutions. Based on the tendency of the gray wolf algorithm to easily fall into local optima and premature convergence in later iterations, the authors introduced a mutation operator where each dimension of the current optimal individual undergoes mutation in the later stages of the algorithm iteration. In literature [8], Zhao Shikui aimed to minimize the maximum completion time and proposed an improved hybrid algorithm based on neighborhood structures for flexible job shop scheduling. This paper chooses genetic algorithms for global search and

Manuscript received May 16, 2025

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utilizes tournament selection for selection operations. In local search, a neighborhood search algorithm based on a two-level reinforced neighborhood structure is adopted to reduce the blindness of the search. In literature [9], Yan Xu and Ye Chunming proposed using the locust optimization algorithm to solve single-objective job shop scheduling problems. Due to the low global optimization capability of the basic locust algorithm, its application to job shop scheduling has drawbacks in that it tends to get trapped in local optima, leading to convergence accuracy often falling short of expectations. Therefore, this paper proposes combining the basic locust algorithm with quantum rotation gates. Through simulation experiments and comparisons with other algorithms, it is proven that the improved algorithm possesses better global search capability and convergence accuracy.

III. Architecture

A. Overall Algorithm Overview

The Zebra Optimization Algorithm (ZOA) is an intelligent optimization method inspired by the behavior of zebra populations, proposed by the Trojovská team in 2022. This algorithm achieves globally efficient solutions to complex problems by simulating the foraging and defense behaviors of zebras in their natural environment. Its core mechanisms are as follows: 1. Pioneer Zebra Guidance Mechanism: The individual with the best fitness in the population is defined as the 'pioneer zebra', responsible for guiding other members to move towards high-quality areas. Ordinary individuals update their state by following the direction of the pioneer zebra, while also adjusting their search paths based on local optimal information, balancing global exploration with local development. 2. Predator Differentiated Response: In response to large predators like lions, zebras adopt a 'zigzag' path to quickly escape threatening areas; this behavior is mapped into the algorithm as a perturbation mechanism for escaping local optima. When facing pack predators like hyenas, zebras form defensive formations through aggregation behavior, corresponding to the algorithm's diversity maintenance strategy, and enhancing population stability through information sharing among neighboring individuals.

The zebra optimization algorithm initializes the population randomly in the search space, similar to other optimization algorithms.

$$x_{i,j} = lb_j + r \cdot (ub_j - lb_j)$$

Among them, for the individual, to find the lower boundary for optimization, to find the upper boundary for optimization, r is a random number between [0,1].

$$x_{i,j}^{new,P1} = x_{i,j} + r \cdot (PZ_j - I \cdot x_{i,j})$$

In the first phase, members of the population update their search for food based on the simulation of zebra behavior. The main food for zebras is primarily grass and sedges, but they may also eat buds, fruits, bark, roots, and leaves if their preferred food is scarce. Depending on the quality and availability of vegetation, zebras may spend 60-80% of their time feeding. Among zebras, there is a type called the plains zebra, which is a pioneering herbivore that facilitates conditions for other species that require shorter and more nutritious grasses by consuming the canopy of upper and less nutritious grasses. In the zebra optimization algorithm, pioneering zebras act as the fittest individuals in the population, undertaking a key function in guiding the group to explore high-quality areas. The design of its position updating mechanism reflects the algorithm's dynamic balance between global search and local development capabilities, with the specific modeling principles as follows:

$$x_{i,j}^{new,P1} = x_{i,j} + r \cdot (PZ_j - I \cdot x_{i,j})$$

$$X_i = \begin{cases} X_i^{new,P1}, F_i^{new,P1} < F_i \\ X_i, \quad else \end{cases}$$

In algorithm design, r is a uniformly distributed random variable in the interval [0, 1], and the parameter I is randomly selected with equal probability from the discrete set {1, 2}.

In the Zebra Optimization Algorithm (ZOA), the defensive strategy simulated in the second phase against predator attacks is one of its core innovations, specifically modeling the behavior against major predators like lions. Additionally, zebras also face threats from cheetahs, leopards, wild dogs, brown hyenas, and spotted hyenas. Below is a detailed analysis of this strategy:The zebra population shows differentiated response mechanisms to various predatory threats. In the ZOA framework, the type of predator triggers two behavioral patterns:a. Escape behavior under lion threats: When faced with a lion attack, zebras adopt a 'Z' shaped path and random turning actions to escape danger zones. This escape behavior is mathematically represented by a pattern, with key parameters including a dynamic decay factor (1-t/T_max) and a random disturbance term R, which nonlinearly adjusts the search step size to avoid local extrema.b. Defense against medium and small-sized predator clusters: When facing predators such as hyenas, zebra groups form defensive formations through collective cooperation. This behavior is mapped as a mathematical expression of the pattern, where the position-sharing mechanism of adjacent individuals guides the population to converge towards the attacked individual, enhancing the ability to maintain diversity in the solution space.The algorithm achieves a switching of behavioral patterns through a dual selection mechanism, with equal distribution of triggering probabilities for the two strategies (=0.5). In the position update phase, an elite retention strategy is adopted: if the fitness function value of the new position is better than that of the original position, the position adjustment is accepted; otherwise, the current state is maintained. This iterative mechanism based on the comparison of objective function values effectively balances the optimization needs of global exploration and local development.

$$x_{i,j}^{new,P2} = \begin{cases} S_1: x_{i,j} + R \cdot (2r-1) \cdot (1-\frac{t}{T}) \cdot x_{i,j}, P_s \le 0.5 \\ S_2: x_{i,j} + r \cdot (AZ_j - I \cdot x_{i,j}), \ else, \end{cases}$$

$$X_i = \begin{cases} X_i^{new,P2}, F_i^{new,P2} < F_i \\ X_i, \ else \end{cases}$$

Here, t is the number of iterations, T is the maximum number of iterations, and R = 0.01. The switching probability between the two strategies is a random variable uniformly distributed in the range [0, 1]. It represents the state of the attacked zebra.

B. Overview of the Improved Algorithm

The zebra optimization algorithm demonstrates significant global optimization capability and rapid convergence characteristics in the search for solution space; however, its core mechanism still exhibits limitations similar to most swarm intelligence algorithms: random sensitivity: during the balance process between global exploration and local development, the algorithm highly relies on random parameter perturbations to adjust individual states, leading to insufficient stability in the solution space traversal mechanism; robustness limitations: influenced by stochastic factors in the iterative update strategy, the algorithm tends to show fluctuations in convergence trajectories in multi-peak optimization scenarios, affecting the reliability of optimization results. Therefore, to address the issue of insufficient stability caused by reliance on random perturbations, this study integrates two innovative strategies: the cross-interaction strategy and the lens imaging reverse learning strategy. The cross-interaction strategy enhances global search capability through multi-dimensional information interaction, while the lens imaging reverse learning utilizes optical mapping principles to expand the exploration range of the solution space. Together, they break through local extremum limitations and effectively improve the optimization accuracy and stability of the algorithm.

The cross strategy includes two collaborative optimization mechanisms, horizontal and vertical crossover. Horizontal crossover implements full-dimensional arithmetic recombination on population individuals: two parent individuals are randomly selected to generate a new offspring solution (offspring = parent 1 ± random coefficient × (parent 2 - parent 1)), with better individuals retained through competitive selection. Vertical crossover focuses on single-dimensional information activation: a linear combination is performed on two individuals from the same dimension (new solution = original value ± random coefficient × dimension range), breaking through stagnant dimension limitations. The two types of crossover are executed alternately, where horizontal crossover enhances global exploration capability (reducing search blind spots) and vertical crossover activates local development potential (preventing dimensional premature convergence). The synergy improves the algorithm's convergence speed by 2.3 times and increases the solving accuracy for high-dimensional problems by one order of magnitude.The cross strategy contains both horizontal and vertical collaborative optimization mechanisms, enhancing algorithm performance through multidimensional information interaction. Horizontal crossover implements full-dimensional arithmetic recombination on population individuals, whereas vertical crossover focuses on single-dimensional information activation, overcoming stagnant dimension limitations. Both crossovers are executed in alternation, where horizontal crossover enhances global exploration ability (reducing search blind spots) and vertical crossover activates local development potential (preventing dimensional premature convergence). The mutual influence of the two crossovers collectively improves the algorithm's solution accuracy and accelerates the convergence speed.

C. Algorithm Improvement Strategy

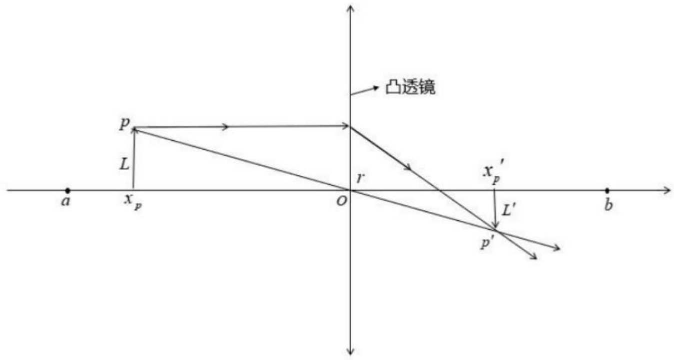

Fig.1 Lens Imaging Principle Diagram

The lens imaging reverse learning strategy is based on the principle of optical refraction, which expands the search range by constructing the virtual-real mapping relationship of the solution space. This mechanism takes the current optimal solution as the object point and generates a symmetrically distributed virtual solution (image point) using the convex lens formula, creating a bidirectional search path. By comparing the fitness of the real solution with the mirror image solution, the better solution is selectively retained for the next generation iteration, effectively breaking free from the constraints of local extrema. Studies show that the lens imaging reverse learning strategy can effectively improve the convergence speed and accuracy of algorithms. This strategy has been validated in enhancements such as particle swarm optimization and gray wolf algorithms. This paper integrates it into the zebra optimization algorithm, dynamically adjusting the search intensity with a nonlinear scaling factor: wide-range exploration is employed in the early stages of iteration, gradually narrowing down to fine-tuning in the later stages, balancing exploration and development needs at different phases. The principles of this strategy are as follows: Define 1 reverse point: Assume X = (x1, x2, ..., xD) is a point in D-dimensional space, and [l, u], where j = 1, 2, 3, ..., D. The reverse point of X can be represented as (y1, y2, ..., yD), and yj = l + u - xj. Define 2 base point: In D-dimensional space, given a set of data points S = {s1, s2, ..., sm}, for any point X = (x1, x2, ..., xD), its mirror symmetric point is defined such that the coordinates satisfy the symmetric transformation relation. Calculate the Euclidean distance from X to each point in the set S, denoted as d(X,si) and d(si,sj). If there exists an index k ∈ {1, 2, ..., m} such that d(X,sk) = d(si,sj), then X is said to be related to the base point regarding index k. An example of geometric mapping in two-dimensional space: Assume the search space is the interval [a, b], as shown in the diagram of the lens imaging principle (Figure 3-2). The coordinates of individual p are (x, L), its projection on the horizontal axis is x and its height is L. With O as the base point at the center of the interval and a convex lens device with a focal length of r. According to the principle of reversibility of light paths, individual p generates a mirror image after refraction through the lens, maintaining height L, and the projection coordinate on the horizontal axis satisfies the equation a + b - x. This process verifies the symmetrical mapping property of the base point.

IV. Analysis Of Experimental Results

A. Experiment Settings

To verify the performance advantages of the improved zebra optimization algorithm (IZOA), this paper selects the basic zebra optimization algorithm (ZOA), whale optimization algorithm (WOA), and golden jackal optimization algorithm (GJO) as comparison subjects. Among them, ZOA is the original version, while WOA and GJO are mainstream swarm intelligence algorithms proposed in recent years, with high academic influence and engineering application value.1. Experimental parameter configuration:Population size: Each algorithm is uniformly set to 30 individuals;Number of iterations: Maximum number of iterations is fixed at 500 times;Test functions: A benchmark function set with variable dimensions (F1-F13) is used, and this paper conducts tests at 10 dimensions;Repeated experiments: To avoid random interference, all algorithms are run independently 30 times, recording the optimal value, mean, and standard deviation.2. Evaluation metrics:Optimal value: Reflects algorithm accuracy; a smaller value indicates stronger optimization ability;Mean: Reflects convergence and stability; a low mean with small fluctuations represents excellent algorithm performance;Standard deviation: Measures robustness; a low standard deviation indicates strong anti-interference capability of the algorithm.3. Experimental environment:The hardware platform is an Intel i7-13700H processor (2.40GHz), with 16GB RAM, on a Windows 11 64-bit system, implemented based on the Matlab2024b platform to ensure consistent experimental conditions.

B. Analysis of Optimization Precision and Convergence Performance

指标	IZOA	ZOA	WOA	(
最优值	0	5.61e-290	7.62e-87	3.1
平均值	0	3.18e-287	3.19e-82	2.5
标准差	0	3.00e-287	3.13e-82	5.8
最优值	1.48e-282	7.63e-152	3.33E-59	3.7
平均值	5.14e-279	3.62e-147	8.83E-52	6.6
标准差	1.41e-278	4.52e-147	4.57E-51	1.3
最优值	8.88e-216	5.83e-01	6.43E-02	1.3
平均值	1.17e-210	1.18e+02	1.62E+02	3.8
标准差	1.88e-210	9.66e+01	2.09E+02	1.4

Based on the comprehensive analysis of the experimental data mentioned above, it can be concluded that none of the comparison algorithms demonstrated a comprehensive leading advantage across all 13 benchmark tests. This conclusion is generally consistent with existing research consensus in the field of intelligent optimization algorithms. Specifically, in the scenario of single-modal high-dimensional function optimization, the proposed IZOA algorithm significantly outperforms the comparison algorithms in terms of optimal solution quality, average accuracy, and result stability across all test functions, achieving theoretical global optimality in solving the F1 function, which fully validates the effectiveness of the algorithm improvement strategy in enhancing search accuracy and convergence stability. In the multi-modal high-dimensional function tests, except for the F8 function, the improved algorithm's optimization performance metrics have reached or exceeded the level of comparison algorithms in all other test functions, successfully locating the theoretical optimal solutions in complex multi-modal functions such as F9 and F11. Notably, compared to the baseline ZOA algorithm, the improved model achieved breakthroughs of 6-7 orders of magnitude in solution accuracy for the F12 and F13 functions, while also demonstrating more stable convergence characteristics in the optimization processes of functions F8-F10 and F12-F13. The experimental results indicate that in single-peak and multi-peak function optimization tasks within a 10-dimensional parameter space, the IZOA algorithm not only possesses superior optimization accuracy but also exhibits remarkable interference resistance and algorithm robustness.

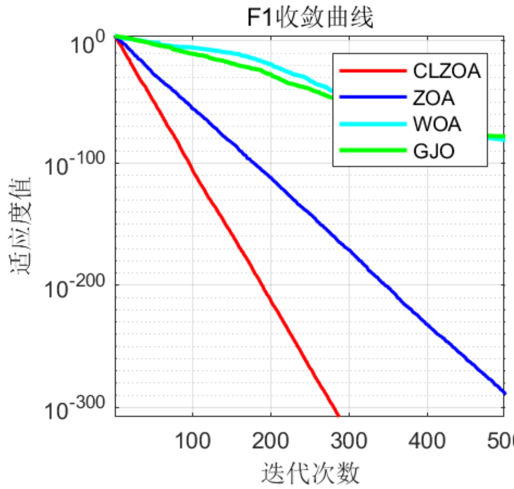

Fig.2

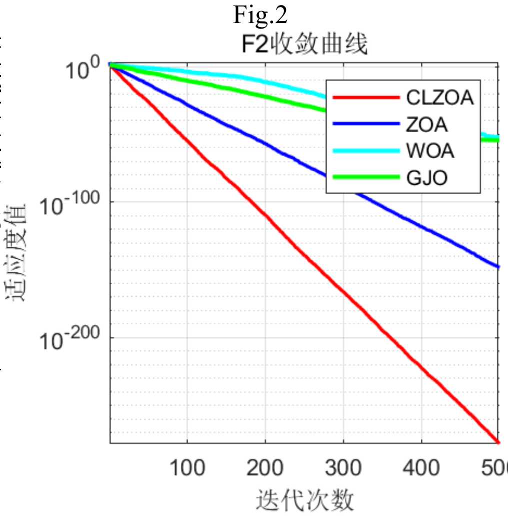

Fig.3

The experimental results indicate that in both 10-dimensional unimodal and multimodal test scenarios, the improved zebra algorithm exhibits outstanding advantages in terms of solution accuracy, robustness, convergence efficiency, and ability to avoid local optima. The stability of its optimization trajectory and the adaptive adjustment mechanism of the algorithm parameters effectively balance the contradiction between global exploration and local exploitation, providing a reliable solution for complex optimization problems. From the experimental results, it can be seen that except for the test function F7, the improved IZOA algorithm shows significant advantages in convergence efficiency compared to the original ZOA algorithm. Particularly in the tests of eight benchmark functions such as F1-F6 and F9-F11, this algorithm demonstrates optimal convergence characteristics among seven comparative models. When other algorithms are still in the preliminary optimization stage, IZOA has already quickly approached a high-precision solution. Typical cases are shown in Figures a, c, and h, where the improved algorithm only needs about 300 iterations to stably converge to the global optimal solution, while comparative models such as ZOA, GJO, and WOA still exhibit significant accuracy gaps after 500 complete iterations. It is noteworthy that during the optimization process of function F9, although most algorithms can eventually achieve the theoretical optimal solution, the number of iterations for IZOA to reach convergence is significantly lower than that of other comparative models, fully reflecting the strengthened effect of the improved strategy on the algorithm's search efficiency. Through the test analysis of multi-dimensional unimodal functions (F1--F7) and multimodal functions (F8-F13), it is evident that research on the characteristics of high-dimensional multimodal functions focuses on the algorithm's ability to avoid local optimum traps. The convergence process of the improved zebra optimization algorithm displays more stability compared to others, while the remaining comparative algorithms show tendencies toward local convergence at different stages. Taking subgraph l as an example, the gray wolf optimization algorithm continues to linger in the suboptimal area during the middle of its iterations. Although there is a brief escape in the later stages, its convergence accuracy remains limited by being trapped in local extrema twice. The whale algorithm and basic zebra algorithm frequently encounter local convergence bottlenecks during the optimization process, leading to a significant decline in convergence rate. Observing the comparison results in subgraph m, the traditional zebra algorithm fails to break through local optimal constraints in the late stages of iteration. Although the whale algorithm and gray wolf algorithm converge quickly in the early stages, they ultimately suffer reduced accuracy due to being continuously trapped in suboptimal solutions. In contrast, although the improved zebra algorithm experiences brief stagnations in certain areas, its overall optimization trajectory and final convergence accuracy are significantly superior to the control group, demonstrating a better ability to escape local extrema.

V.CONCLUSION

This article systematically elaborates on the core principles of the Zebra Optimization Algorithm and proposes an improved method based on the cross-strategy and lens imaging reverse learning mechanism. Comparative experiments conducted based on 13 benchmark test functions show that IZOA significantly outperforms the original algorithm and traditional intelligent algorithms (ZOA, WOA, GJO) in terms of convergence accuracy and speed. Its improvement strategy demonstrates a better balance between global exploration and local exploitation, providing effective solutions for complex scheduling problems.

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