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Multi-Objective Evolutionary Algorithm with Random Disturbance of Different Population Mutation Strategies

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Abstract:

In order to improve the convergence and diversity of the non-dominated solution set of multi-objective optimization problems, and solve the problem that the algorithm is easy to fall into the local optimum in the later stage, according to the characteristics of different differential evolution strategies, an adaptive differential evolution based on the improved Chebyshev mechanism is proposed. Strategy decomposition multi-objective evolutionary algorithm (MOEA/D-ADE-levy). First, the mixed-level orthogonal experiment is used to generate uniform weight vectors and applied to improve the Chebyshev mechanism to decompose the sub-problems to obtain a uniformly distributed initial population; secondly, the population is divided into excellent individuals, intermediate individuals and poor individuals, and different individuals are used. The mutation strategy uses an adaptive mechanism for the mutation factor F and the crossover probability CR to improve the convergence and diversity of the non-dominated solution set; finally, the levy random perturbation is added to the solution set that falls into the local optimum to increase its global search ability. Jump out of the local optimum. The DTLZ test function is used to verify the effectiveness of the algorithm, and the proposed algorithm is compared with common algorithms such as NSGA2, NSGA3, MOEA\D, MOEA\D-DE, etc., and the diversity and convergence analysis of the algorithm is performed using GD and IGD evaluation indicators. The results show that the algorithm has been improved and improved in terms of convergence and diversity, and can obtain a better Pareto solution set.

Keywords: *Hybrid level orthogonality, Chebyshev, Adaptive difference, Local optimum, Convergence, Diversity*

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I. INTRODUCTION

In the real world, the number of objectives for optimization problems is mostly high-dimensional multi-objective problems greater than 4. However, in the optimization of multi-objective problems between different objectives, there are conflicts in the solution sets, and as the number of objectives increases, the number of non-dominated individuals in the population increases rapidly, which weakens the search ability of the algorithm. Multi-objective evolutionary algorithm (MOEA: multi-objective evolutionary algorithm) can find the optimal solution set of a set of balanced decision vectors in a single run. Using MOEA to optimize high-dimensional multi-objective problems is a hot research topic. The current research on high-dimensional multi-objective optimization is mainly carried out from three aspects:

1. The optimization of the operator during the crossover and mutation process of the generated solution. Usually, crossover and mutation operators are often used in the process of generating solutions, such as analog binary crossover, differential mutation, polynomial mutation, etc.; Liu Bin proposed to establish multiple subpopulations to improve local search performance [1], Zheng Jinhua proposed a directional search strategy, It affects the convergence and distribution of the algorithm by influencing the generation area of the individual offspring [2].

2. In the retention solution with high adaptability, when the goals conflict, the basis for the balance between convergence and distribution needs to be considered comprehensively. For the algorithms that retain solutions with high adaptability, the algorithms that consider the convergence and distribution of the solution are currently mainly based on the algorithm based on the dominance relationship, the algorithm based on the decomposition, the algorithm based on the reference point and the algorithm based on the index.

In the algorithm based on the dominance relationship, as the number of targets increases, in order to increase the selection pressure and improve convergence, Yu G proposes α-domination [3], Laumanns proposes ε-domination relationship [4] to determine non-dominated solutions The dominance relationship between the individual, so as to determine the strength of the individual; based on the decomposition algorithm is to decompose a complex high-dimensional multi-objective optimization problem into a set of single-objective optimization problems or easy-to-manage multi-objective problems. For example, Hughes uses MSOPS multiple single-target Pareto sampling to search for all targets in parallel [5], MOEA/D uses a set of weights to decompose a MOP into multiple sub-problems, so that each solution in the population corresponds to a corresponding sub-problem. Viduo objective shows very good

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results [6]; the algorithm based on reference point replaces the original method of calculating the crowding distance by selecting the reference point, which can more effectively improve the diversity of the population. For example, MGSA-NSGA-III hybrid algorithm [7], I-NSGA-II algorithm [8], NSGA-III-RPCDP algorithm [9], etc. all introduce a reference point selection mechanism to improve the adaptability of the population; based on indicators The algorithm finds better individuals by modifying the evaluation index and using the selection mechanism to compare the quality of the solution. Such as IBEA algorithm [10], SMS-EMOA algorithm [11], etc.

Mining effective information in the target space, using methods such as reduction, dimensionality reduction, and high-dimensional preference to collaboratively enhance the evolutionary pressure of algorithms. In the practical application of high-dimensional multi-objective optimization problems, there are: 1. Redundant objectives, that is, not all objectives have conflicts; 2. The objective solution does not have to be the entire Pareto optimal solution set, but a solution that satisfies the demand. Determining the feature extraction and feature selection methods, and giving specific preference information can effectively reduce the search space and improve the search ability of the algorithm. Reddy S R proposed preference optimization based on reference points, by selecting a set of reference points to obtain a Pareto optimal solution set [12]. Brockhoff and Zitzler proposed the s-Moss problem and the k-EMOSS problem that allow small changes in the dominant structure [13]. Fleming et al. proposed to apply the method of clarifying preference information to high-dimensional optimization, so as to continuously determine preference information [14].

The decomposition-based multi-objective evolutionary algorithm (MOEA/D) has been widely used to process MOPS. In 2019, R Tanabe et al. used three index selection methods, two mutation strategies, and five boundary processing methods to select the appropriate The configuration of the MOEA\D-DE operator is used to process mops [15]; Z Zhou et al. proposed a multi-objective genetic algorithm DEA-MOEA/D in 2018, which combines the decomposition method with the data envelopment method and uses the difference calculation method. As an evolutionary operator, it has been compared with other basic algorithms to verify the superiority of this algorithm in dealing with Mops problems [16]; S Zapotecas Martinez et al. proposed to combine the MOEA\D algorithm with the most popular direct search method Nelder and Mead methods. It combines the global search feature of MOEA\D with the development ability of mathematical programming technology. Since the MOEA\D algorithm has proposed many modified versions, some methods aim to obtain better performance by taking advantage of the various scaling functions used in the MOEA/D framework. The search performance of the algorithm is not considered. This article is aimed at MOEA\D. The D framework uses the orthogonal matching algorithm to generate uniform weights, uses the improved Chebyshev formula to decompose the mops problem, divides the population into excellent individuals, intermediate individuals and poor individuals, uses different mutation strategies for different individuals, and determines the mutation factor F and crossover probability CR adopt an adaptive mechanism, and compare the convergence and distribution of the proposed algorithm with NSGA2, NSGA3, RVEA, MOEA\D, MOEA\D-DE, and experiments show that the proposed algorithm can achieve convergence. And the Pareto solution set with better distribution.

II. ALGORITHM DESCRIPTION

The MOEA/D algorithm has been proven to be advanced in convergence and diversity, but it has the problem of easily falling into local optimality [17]. In order to ensure the algorithm's balance between method convergence and diversity, MOEA is proposed. \D-ADE-levy algorithm. In view of the large population of high-dimensional multi-objective problems and the uneven weights generated by the MOEA\D algorithm, the values generated by the hybrid orthogonal level experiment are uniformly dispersed, neat and comparable to produce uniformly distributed weight vectors; Introduce the generated weight vector into the improved Chebyshev decomposition method to decompose the Mops problem into a series of sub-problems; then, in view of the convergence of the offspring generation method and the imbalance in diversity, the offspring are divided into excellent individuals and intermediate individuals For different individuals and poor individuals, use different cross mutation methods to generate offspring. For excellent individuals, strengthen their local search capabilities, and adopt population adaptive evolution strategies for intermediate individuals. According to the number of population evolution, combined with neighbor node information, adaptive Adjust the evolution strategy, improve the individual's global search ability and exploration ability for poor individuals, accelerate the convergence to the optimal solution, and ensure the balance of algorithm convergence and diversity; then combine the characteristics of Levy's large flight jump and long tail, Use levy perturbation for individuals trapped in the local optimum to increase their global search ability and jump out of the local optimum; Finally, the improved Chebyshev function is used as the sorting criterion for individual selection, and the Pareto optimal solution with better convergence and diversity is obtained.

The overall process of the MOEA\D-ADE-levy algorithm is shown in Figure 1:

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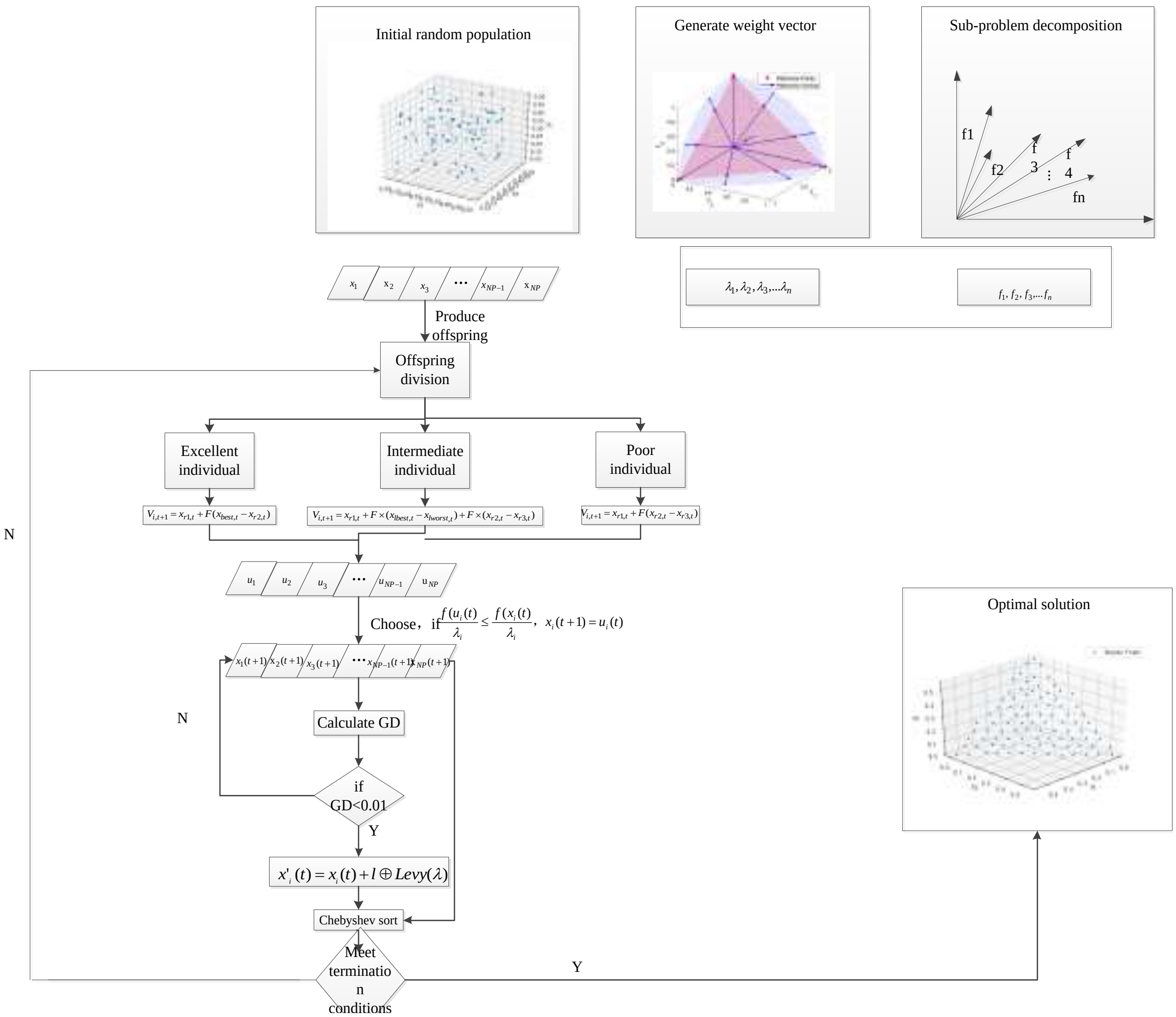

Fig 1: Algorithm flow chart

2.1 Generate Weight

In real life, the preference information of the decision maker is usually unknown. The MOEA\D algorithm first generates a set of uniformly distributed weight vectors, and obtains a solution that can be uniformly distributed on the Pareto front. For a Mops with a population size of N and a target dimension of m, it is N uniformly distributed weight vectors generated by MOEA\D. For any component in the weight vector $\lambda^i = (\lambda_1^i, \lambda_2^i, \cdots \lambda_m^i)$, the value is not repeated from $\left(0, \frac{1}{H}, \frac{2}{H}, \ldots \frac{H}{H}\right)$, and N is obtained by the following formula:

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$$N = C_{H+\mathrm{m}-1}^{m-1} \tag{1}$$

It can be seen from the formula that as the target dimension increases, the number of N will continue to increase. Table I shows the change of N under different (H, m) situations.

Table I. Changes of N under different (H, m)

m			**H**		
	6	12	18	24	30
4	84	455	1330	2925	5456
6	462	6188	33649	118755	324632
8	1716	50388	480700	2629575	10295472
10	5005	293930	4686825	38567100	211915132
15	34453	8584622	419053867	8.60E+09	1.02E+11

It can be seen from the table that as (H, m) increases, N increases exponentially. The MOEA\D algorithm to generate uniform weights is not suitable for high-dimensional multi-objective problems. The orthogonal level experiment is based on the comprehensive. In the experiment, some representative points are selected for the experiment, and these points have the characteristics of uniform dispersion and neatness and comparison. Therefore, the orthogonal experiment method is used to generate the initial population to obtain the uniform distribution of the initial points. In this paper, the mixed level orthogonal method [18] is used to generate uniform the weight λ, its algorithm flow is shown in Table II:

Table II. Mixed horizontal orthogonal

Input	**Population size: N; Number of targets: m; Orthogonal index: J1, J2; Mixed level orthogonal table division level Q1, Q2; Horizontal orthogonal table division level Q**
Output	N uniformly distributed weight vectors
1	for (k=1,k≤J,k++)
2	$j=(Q^{k-1})/(Q-1)+1$ $j=(Q^{k-1})/(Q-1)+1$
3	for (i=1,i≤Q^j,i++)
4	$a_{i,j}=\left\lfloor \frac{i-1}{Q^{J-k}} \right\rfloor \bmod Q$ $a_{i,j}=\left\lfloor \frac{i-1}{Q^{J-k}} \right\rfloor \bmod Q$
5	end
6	end

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```
for (k=2,k≤J,k++)
    j=(Q^{k-1})/(Q-1)+1  j=(Q^{k-1})/(Q-1)+1
for (s=1,s≤j-1,s++)
    for (t=1,t≤Q-1,t++)
        a_{j+(s-1)(Q-1)+t}=(a_s×t+a_j) mod Q  a_{j+(s-1)(Q-1)+t}=(a_s×t+a_j) mod Q
        end
end
end
a_{i,j}=a_{i,j}+1, i∈[1:M]∧j∈[1:N]  a_{i,j}=a_{i,j}+1, i∈[1:M]∧j∈[1:N]
Construct an equal-level orthogonal table L_{M_1}(Q_1^{N_1})=(a_{i,j})_{M_1×N_1}   L_{M2}(Q_2^{N_2})=(b_{i,j})_{M_2×N_2}
for (k=0,k<M_1,k++)
  for (i=0,k<M_2,i++)
    c_{(k-1)M2+i}=[a_k,b_i]
Output mixed horizontal orthogonal matrix c(i,j)_{M*(N_1+N_2)}
Uniformly sample the mixed level orthogonal table to obtain N uniformly distributed weight vectors
```

In Algorithm 1, an equal-level orthogonal table is first constructed: $L_{M_1}(Q_1^{N_1})=(a_{i,j})_{M_1\times N_1}$ and $L_{M2}(Q_2^{N2})=(b_{i,j})_{M2\times N2}$, in which, $M=M_1\times M_2, M_1=Q_1^{J_1}, M_2=Q_2^{J_2}$, $\begin{cases}\frac{Q_1^{J_1}-1}{Q_1}\geq N_1\\ \frac{Q_2^{J_2}-1}{Q_2}\geq N_2\end{cases}$ and then a mixed horizontal orthogonal matrix $(c_{i,j})_{M\times(N_1+N_2)}$ is obtained through iteration, and finally N uniformly distributed weight vectors λ are obtained. In this paper, the values of J1 and J2 are 1 and 2 respectively.

2.2 Target Decomposition

The MOEA\D algorithm decomposes the Mops problem into a series of sub-problems. The optimal solution of each sub-problem corresponds to a Pareto optimal solution of the original Mops problem. The commonly used decomposition methods are: 1. Weighted sum method, which is simple to solve. However, it is difficult to find the optimal solution when the multi-objective problem is non-convex; 2. The boundary intersection method, although it can find a uniform Pareto solution set, it needs to deal with the equality constraints and the penalty coefficient θ value needs to be set in advance; 3. Chebyshev method, although this method can solve the non-convex problem, but under the uniformly distributed weight vector, the optimal

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solution of the sub-problem under the Tchebycheff decomposition scheme is not very uniform. This paper uses an improved Tchebycheff decomposition method, the formula is as follows:

$$\min g^{te}(x \mid \lambda, z^*) = \max_{1<j<n} \left\{ \frac{\left| f_j(x) - z_j^* \right|}{\lambda_j} \right\} = \max_{1<j<n} \left\{ \frac{f_j(x) - z_j^*}{\lambda_j} \right\} \quad (2)$$

$$subject\ \ to\ x \in \Omega$$

For a straight line $\frac{f_1(x)-z_1^*}{\lambda_1} = \frac{f_2(x)-z_2^*}{\lambda_2} = \cdots \frac{f_m(x)-z_m^*}{\lambda_m}$, under ideal conditions, there is an intersection with PF, which is the Pareto optimal solution. The improved Tchebycheff decomposition method can not only solve the non-convex problem, but also obtain a uniformly distributed solution.

2.3 Generation of Offspring

The generation strategy of the offspring has an important influence on the search of the algorithm. When the evolutionary algorithm solves the optimization problem of high-dimensional multi-peak complex function, there are problems such as easy to fall into the local optimum, premature convergence, and slow convergence speed in the later stage, which leads to it is difficult to solve the problem in practical engineering applications with high scale, high nonlinearity, and high real-time requirements. Therefore, a MOEA/D-ADE-levy algorithm is proposed. First, all individuals in the population are divided into excellent individuals, intermediate individuals and poor individuals. The excellent individuals and the poor individuals are from the top and bottom 100p% individuals in the current size NP population respectively. This article has been verified by experiments, when the ratio of the three individuals is 1/4, 1/2, 1/4, the algorithm has the best performance. Different selection operators are performed on the three kinds of individuals. The excellent genes in the individual should be retained as much as possible for the outstanding individuals, and the ability of local search should be strengthened. The population adaptive evolution strategy is adopted for the intermediate individuals. The evolution times, combined with neighbor node information, adaptively adjust the evolution strategy, and improve the individual's global search ability and exploration ability for poor individuals, and accelerate the convergence to the optimal solution. Secondly, it is proposed to use the era distance (GD) to judge whether the population falls into the local optimum. Add levy random perturbation to the solution falling into the local optimum,

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increase the global search ability of the algorithm, and avoid the population falling into the local optimum; finally, the optimal Pareto solution set is selected by improving Chebyshev's fitness sorting. The detailed process is as Table III Shown:

Table III. MOEA\D-ADE-levy algorithm

MOEA\D-ADE-levy	
Input:	Multi-objective optimization problem; algorithm termination condition; population size N; initial weight vector: the number of weight vectors T in each neighborhood of λ;
Output:	Optimal solution
1	Calculate the Euclidean distance between any two weights, and find T weight vectors that are close to each weight vector, $B(i)=\{i_1,...i_T\}$,$i=1,2,...n$,$\lambda_{i1},...\lambda_{iT}$ are T similar weight vectors of λ_i
2	Randomly generate initial population in feasible space$\{x_1,x_2,...x_n\}$
3	Initialize $z=\{z_1,z_2,...z_m\}$,$z_i=\min\{f_i(x_1),f_i(x_2),...f_i(x_N)\}$
4	Set EP to empty
5	for *i*=1,...N,do
6	Divide the population into excellent individuals x_{best}, Intermediate individual x_{middle} and poor individuals x_{worst}
7	if x ∈ x_{best}
8	$V_{i,t+1} = x_{r1,t} + F(x_{best,t} - x_{r2,t})$
9	if x ∈ x_{middle}
10	$V_{i,t+1} = x_{r1,t} + F \times (x_{lbest,t} - x_{lworst,t}) + F \times (x_{r2,t} - x_{r3,t})$
11	else
12	$V_{i,t+1} = x_{r1,t} + F(x_{r2,t} - x_{r3,t})$
13	Mutation: $U_{i,t+1}$ are generated by applying repair and improvement based on test problems to $V_{i,t+1}$
14	for each j=1,2,...m,if $z_i<f_j(U_{i,t+1})$ end for
15	Update neighborhood solution
16	Calculate the generation distance between two adjacent populations
17	if GD<0.01
18	Random perturbation using levy, $V_i^{'}(t) = V_i(t) + l \oplus Levy(\lambda)$
19	if $z_i<f_j(V_i^{'}(t))$ end for
20	Update neighborhood solution

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21	Update EP, remove all vectors dominated by F(y) from EP, if all vectors in EP are not dominated by F(y), then add F(y) to EP
22	Meet the termination condition: stop and output EP, otherwise go to 5

Through the above-mentioned progeny generation method, the mutation mode of the individual in each generation of the population during the evolution process is adjusted in a targeted manner, which is more suitable for the individual's own evolutionary needs, and avoids the defects of large calculation amount and slow convergence speed caused by blind search. Therefore, the overall convergence speed of the population is accelerated, and the balance between population convergence and diversity is achieved.

For excellent individuals, because they retain their excellent genes and strengthen their local search capabilities, the following formula is used to generate offspring individuals:

$$V_{i,t+1} = x_{r1,t} + F(x_{best,t} - x_{r2,t})$$
$$U_{i,t+1} = \begin{cases} V_{i,t+1}, rand(j) \le CR \\ x_{i,t}, others \end{cases} \quad (3)$$

Where, $x_{r1,t}, x_{r2,t}$ is the randomly selected child base vector, $x_{best,t}$ is the optimal individual in the t-th generation population, F is the scaling factor, CR is the crossover probability, and the scaling factor F determines the degree of perturbation of the difference vector to the base vector in the mutation operation. When the value of F is small, the degree of population difference decreases, so that the population can quickly search for the optimal value in its local range. The crossover probability factor CR controls the proportion of the variant individuals in the test individuals generated by the crossover operation, that is, the test individuals Which components are contributed by the mutation vector and which components are contributed by the target vector. When the CR is large, the proportion of the mutated individuals in the test individuals is larger, which is conducive to local search and accelerate the convergence speed. Therefore, this article sets F for excellent individuals Is 0.9, and CR is set to 0.1.

For the intermediate individual, it means that the fitness value of individual i is at the average level of the population. At this time, the values of F and CR should be adjusted adaptively according to the evolutionary algebra, and the evolution strategy should be adjusted according to the neighbor node information. The formula for generating offspring is:

$$v_{i,t+1} = x_{r1,t} + F \times (x_{lbest,t} - x_{lworst,t}) + F \times (x_{r2,t} - x_{r3,t})$$

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$$U_{i,t+1} = \begin{cases} V_{i,t+1}, rand(j) \le CR \\ x_{i,t}, others \end{cases} \tag{4}$$

Where, $x_{r1,t}, x_{r2,t}, x_{r3,t}$ is the randomly selected child generation basis vector, $x_{lbest,t}, x_{lworst,t}$ are the best and worst individual in the neighborhood, and the target vector is derived from the best and worst individuals among the adjacent M individuals in each generation. Ensuring that the algorithm avoids the worst individuals and guiding the search process in promising areas in the search space improves its local development capabilities. In addition, by using local extrema instead of global extremum, it is ensured that the algorithm avoids the premature convergence of local optimal, because it can prevent all individuals from being affected by the same extremum and increase global interference. In the early stages of the evolutionary process, the number of suitable new individuals (that is, those individuals who are more adaptable than the current individuals) is large. During this period, F should be large to ensure better retention of chromosomes. This will enhance the global search capabilities. In the later stage of the evolution process, F should be reduced to increase the convergence speed. Therefore, F should be set as follows:

$$F = \begin{cases} F_{\max}, & if\ 1 - \dfrac{Gm}{0.1 + Gm - G} > F_{\max} \\ F_{\min}, & if\ 1 - \dfrac{Gm}{0.1 + Gm - G} < F_{\min} \\ e^{1 - \frac{Gm}{0.1 + Gm - G}}, & other \end{cases}$$

$$F \in [0.1, 0.9] \tag{5}$$

When CR is large, although this helps to improve the convergence speed, it may reduce the stability of the algorithm. On the other hand, a small CR value may reduce the ability to explore and open new search spaces. In the early stage of the evolution process, the CR setting is smaller to ensure the diversity of the population, and the later CR is larger to speed up the convergence speed:

$$CR = (1 - e^{1 - \frac{G_m}{0.1 + G_m - G}}) \times (CR_{\max} - CR_{\min}) + CR_{\min} \tag{6}$$

For poor individuals, their global search capabilities should be enhanced to ensure population diversity. The following formula is used to generate offspring individuals:

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$$V_{i,t+1} = x_{r1,t} + F(x_{r2,t} - x_{r3,t})$$
$$U_{i,t+1} = \begin{cases} V_{i,t+1}, rand(j) \le CR \\ x_{i,t}, others \end{cases} \tag{7}$$

Where, $x_{r1,t}, x_{r2,t}, x_{r3,t}$ is the randomly selected basis vector of the offspring. When the value of F is larger, the random perturbation added to the basis point vector is larger, and the population diversity declines slowly, which ensures the population diversity. When the CR is small, the experiment. The proportion of mutant individuals among individuals is small, while the proportion of parent target individuals is larger, which is conducive to maintaining the diversity of the population and global search. Therefore, this paper sets the F of the poor individuals to 0.9 and the CR to 0.1.

Considering that the mutated individual will fall into the local optimum, some scholars determine whether the current population falls into the local optimum by defining the generation distance between two adjacent generations in the population [19], and then decide whether to perform certain operations to avoid Local optimal problem. The distance between two adjacent generations reflects the current search ability of the algorithm to a certain extent. The smaller the distance, the weaker the search ability of the algorithm. The calculation method of the generation distance is:

$$GD(t) = \frac{1}{NP}\sqrt{\sum_{i=1}^{NP} S((x_i(t) - x_i(t-1))^2} \tag{8}$$

This paper experimentally verifies that when the generation distance is less than 0.01, the population falls into the local optimum, and the levy random perturbation is used to jump out of the current local optimum solution. Levi flight is a random movement process that obeys the levy distribution. Continuous large jump behavior, and the jump length has the characteristics of long tail distribution [20]. By introducing Levy flight, the global search capability can be greatly increased, which is conducive to escape from the local optimum. When the population falls into the local optimum, Levy random perturbation is added to the current solution:

$$x'_i(t) = x_i(t) + l \oplus Levy(\lambda) \tag{9}$$
$$l = 0.01(x_i(t) - x_b(t)) \tag{10}$$

In the formula, *Xi(t)*represents the i-th solution of the t-th generation; $\oplus$ represents the dot product; *l* represents the weight of the control step, and x_b is the current optimal solution;

Levy flight Levy(λ) satisfies:

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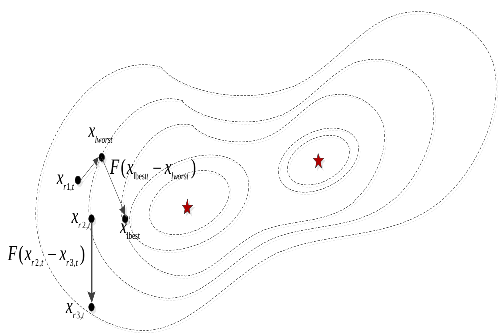
$$Levy(\lambda) = \frac{\mu}{|v|^{\frac{1}{\beta}}} \tag{11}$$

In the formula,ß =2/3, u,v obey normal $u \sim N(0,\delta_u^2), v \sim N(0,\delta_v^2)$ distribution,

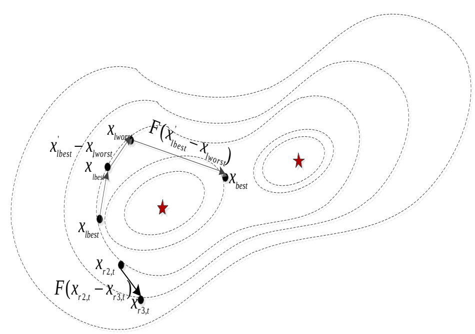
$$\begin{cases} \delta_\mu = \left\{ \dfrac{\Gamma(\beta+1)\sin(\pi\beta/2)}{|\Gamma(\beta+1)/2| * 2^{(\beta-1)/2}\beta} \right\}^{1/\beta} \\ \delta_v = 1 \end{cases} \tag{12}$$

Γ is the standard Gamma function.

Take the search process of the intermediate individual as an example. As shown in the Figure2, in the early stage of the evolution process, the population finds the best point of x_{lbest} along with the evolutionary algebra and falls into the local optimum. At this time, add random Levy perturbation to the current solution to get x'_{lbest}, around x'_{lbest} searches to find the best point x_{best}.



(a)Fall into local optimum



(b) Jump out of the local optimum

Fig 2: Local search changes

2.4 Algorithm Complexity Analysis

The computational cost of the algorithm in this paper comes from the generation of offspring and individual selection in the adaptive differential evolution algorithm. The time complexity calculation includes population division and Chebyshev sorting. M is the target

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dimension, N is the population size, and T is the neighborhood size. The time complexity of Chebyshev sorting is O(MNT), and the complexity of population division is O(N), so the time complexity of the MOEA/D-ADE-levy algorithm is O(N)+O(MNT); The algorithm is compared with NSGA2, NSGA3, RVEA, MOEA\D, MOEA\D-DE algorithm in time complexity, NSGA2 and NSGA3 algorithms both use non-dominated sorting, and the time complexity is O(MN2) [21]; RVEA algorithm uses elite Retention strategy, the time complexity is O(MN2) [22]; the time complexity of MOEA\D and MOEA\D-DE algorithms is mainly generated by Chebyshev sorting to O(MNT), because the neighborhood size T is much smaller than N Therefore, the time complexity of the MOEA/D-ADE-levy algorithm is lower than that of the SGA2, NSGA3, and RVEA algorithms, and its time complexity is slightly higher than that of the MOEA\D and MOEA\D-DE algorithms.

III. EXPERIMENT AND RESULT ANALYSIS

In order to test the performance of the MOEA\D-ADE-Levy algorithm, this experiment uses the NSGA2, NSGA3, RVEA, MOEA\D, MOEA\D-DE algorithm and the MOEA/D-ADE-levy algorithm to analyze the convergence and diversity of the algorithm. The experimental data set uses DTLZ [1-7], and the evaluation method selects GD (Generational Distance) and IGD (Inverted Generational Distance). Regarding convergence and comprehensiveness as evaluation criteria, GD tests the ability of the population to converge in the optimization process, which means the average minimum distance from each point in the solution set to the point in the reference set. The smaller the GD value, the better the convergence. IGD represents the average value of the distance from each reference point to the nearest solution. The smaller the IGD value, the better the overall performance of the algorithm and the better the overall effect.

3.1 Test Function

DTLZ [1-7] is one of the most extensive test sets used to evaluate the performance of high-dimensional MOEAs. The number of targets can be set arbitrarily, and it has the characteristics of linearity, convexo-concave surface, multimodality, degeneracy, and continuous discontinuity [21], so the experiment uses DTLZ [1-7] for algorithm comparison and performance analysis. In the test set, in a given M target test, the decision variable of each objective function is n=m+r-1. When the test problem is divided into 4, 5, 8, 10, 15 goals, that is: $m \in \{4,5,8,10,15\}$, for DTLZ1 set r=5, DTLZ [2-6] set r=10, DTLZ7 set r=20. In order to ensure the fairness of the algorithm, the experimental parameters are set according to the reference [21].

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3.2 Comparative Analysis of Results

Table IV. GD evaluation form

Test question	**Target dimension**	**NSGA2**	**NSGA3**	**RVEA**	**MOEA\D**	**MOEA\D-DE**	**MOEA/D-ADE-levy**
DTLZ1	4	0.880791099	0.005627682	0.005118471	0.00375374	0.000798497	**0.000784916**
	5	0.042263989	0.001661903	0.001647863	0.00647831	0.00269231	**0.000271249**
	8	0.880791099	0.005627682	0.005118471	0.00835897	0.00773183	**0.000723429**
	10	30.80281228	0.011878339	0.003557074	0.00846415	0.00549487	**0.00296237**
	15	28.87207102	0.031268752	0.260981498	0.229494	0.0102717	**0.0108203**
DTLZ2	4	0.233220975	0.023049265	0.023619772	0.0246087	**0.0024612**	0.00246304
	5	0.010135712	0.005422931	0.005418818	0.0569506	0.00904529	**0.00903914**
	8	0.233220975	0.023049265	0.023619772	0.0617011	0.0234301	**0.0234029**
	10	0.239139969	0.012878983	0.004636618	0.0735478	**0.00238418**	0.00253116
	15	0.248723212	0.028313177	0.048543871	0.0650795	0.0224752	**0.0191037**
DTLZ3	4	3.027660735	0.556939368	0.261904907	0.67323	0.352584	**0.00926014**
	5	9.381327835	2.810334421	0.225478763	0.0713153	**0.00805999**	0.126831
	8	188.8520129	0.556939368	0.261904907	0.0343416	0.00239997	**0.00207519**
	10	198.0889519	9.561729661	0.136158031	0.0895757	0.00253573	**0.00223024**
	15	203.5835176	28.11197657	9.449089907	0.0379488	0.411894	**0.0010824**
DTLZ4	4	0.231544268	0.014689941	0.021484742	0.00412767	0.00187433	**0.00189128**

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	5	0.01054476	0.005375725	**0.004679606**	0.00826735	0.0070821	0.0081014
	8	0.231544268	0.014689941	0.021484742	0.0121949	**0.00467712**	0.0127402
	10	0.237360235	0.010065021	0.007590212	0.016955	0.00669059	**0.00656152**
	15	0.25028581	0.023009281	0.0304	0.011933	0.0112459	**0.00652705**
DTL Z5	4	0.221188895	0.14562674	**0.000227974**	0.018932	0.0177899	0.0180423
	5	0.168587249	0.101063921	0.226379077	0.0204437	0.00962639	**0.00297183**
	8	0.221188895	0.14562674	0.00227974	**6.08306E-06**	0.00435803	0.005514
	10	0.259178506	0.127647704	0.0000148	3.91304E-06	0.0259464	**2.37794E-06**
	15	0.272559643	0.058253346	0.0000132	8.66289E-05	2.63228E-06	**1.48863E-06**
DTL Z6	4	0.999991084	0.347856089	0.431048855	**0.0143343**	0.065947	0.036042434
	5	0.755119118	0.235597591	0.377715071	0.0273999	**0.0251974**	0.029912467
	8	0.999991084	0.347856089	0.431048855	3.77134E-06	**3.61259E-06**	0.0361259
	10	1.020857058	0.659018121	0.592402932	**2.02379E-06**	0.0173327	0.0173327
	15	1.038889843	0.960635282	0.006544967	**3.15894E-06**	0.0171394	0.0171394
DTL Z7	4	1.058477795	0.099055032	0.097582392	**0.00925863**	0.00634305	0.020537415
	5	0.046090274	0.012653218	0.040521064	0.0361339	0.0369705	**0.024302967**
	8	1.058477795	0.099055032	0.097582392	0.0698309	0.0933212	**0.020537415**
	10	2.012717164	0.108226792	0.07303261	0.103312	0.0203194	**0.00000226**
	15	2.0127	0.1082	0.073	0.0315894	0.0171394	**0.00366**

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In the Table IV, for each specific data value, in all algorithms, if it is the best, it is expressed in bold font, while the sub-optimal data value is underlined. Subsequent related tables are also expressed in the same way. When the test function is DTLZ1, MOEA/D-ADE-levy has the smallest GD value, indicating that its convergence is the best; on the test function DTLZ2, the GD value is second only to the optimal value in the 4th and 10th dimensions. The dimensions are optimal; in the test function DTLZ3, the performance is slightly worse when the dimension is 5, and the smallest GD value is obtained in the other dimensions; in the test functions DTLZ4 and DTLZ5, the algorithm is on 4, 8 dimensions The GD value of is second only to the optimal value, and is optimal in other dimensions; when the test function is DTLZ6, this algorithm only obtains the sub-optimal GD value when the dimension is 15 dimensions, and the performance is slightly worse; in the test function DTLZ7. This algorithm obtains the sub-optimal GD value in 4 dimensions, and is optimal in other dimensions. Among the 35 data comparisons, the algorithm has 22 values that are optimal, and 5 values are sub-optimal.

Table V. IGD Evaluation Form

Test question	**Target dimension**	**NSGA2**	**NSGA3**	**RVEA**	**MOEA\D**	**MOEA\D-DE**	**MOEA/D-ADE-levy**
DTLZ1	4	3.637021108	0.134441418	0.151745589	0.0612537	0.0481956	**0.0477106**
	5	0.314590684	0.068925063	0.068495392	0.0900173	0.0872355	**0.0651727**
	8	3.637021108	0.134441418	0.151745589	0.112689	0.108406	**0.106926**
	10	24.57655326	0.182866721	0.162439407	0.149439	0.14291	**0.124849**
	15	15.63586278	0.18140408	0.616997079	0.676458	0.293654	**0.151368**
DTLZ2	4	2.280709732	0.386762361	0.387245692	0.135016	0.140305	**0.135016**
	5	0.242263661	**0.212222853**	0.212264285	0.432274	0.279115	0.219918
	8	2.280709732	0.386762361	0.387245692	0.273851	0.387008	**0.273851**
	10	2.259641624	0.67945196	0.527644928	0.43509	0.503364	**0.43509**
	15	2.57174	0.86050	1.00321	0.55884	0.702309	**0.558843**

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		8902	1141	2843	3		
DTL Z3	4	1.096196863	3.86585602	2.228896265	0.0751689	2.21226	**0.0751689**
	5	2.178063671	2.641982192	2.098320878	0.115249	0.280874	**0.115249**
	8	1431.621687	3.86585602	2.228896265	0.12683	1.19117	**0.12683**
	10	1098.509288	24.32808396	1.31016136	0.218434	1.21662	0.218434
	15	1347.730334	39.8388583	41.22784306	0.269203	3.21541	**0.269203**
DTL Z4	4	2.279160051	0.574819437	0.47989729	**0.218324**	0.456473	0.218324
	5	0.24276628	**0.212249087**	0.427213412	0.405716	0.595863	0.380548
	8	2.279160051	0.574819437	0.47989729	0.539032	1.21394	**0.488796**
	10	2.360990549	0.709544748	**0.554689273**	0.840542	0.696964	0.615418
	15	2.634403075	0.821099629	**0.705940259**	1.22344	0.938321	0.885029
DTL Z5	4	0.327683593	0.191893099	0.669559181	0.166166	0.0361721	**0.0352063**
	5	0.078242185	0.12491022	0.119423795	0.379274	0.0355362	**0.025113952**
	8	0.327683593	0.191893099	0.669559181	0.233671	0.0579315	**0.0453433**
	10	0.625829336	0.139370956	0.302475746	0.823062	0.0737306	**0.0733751**
	15	0.832645941	0.170742272	0.451227095	0.3215	0.218515	**0.073697104**
DTL Z6	4	7.995241156	0.830631912	0.267385126	0.057184446	0.036184	**0.0360265**
	5	3.286678282	0.164473955	0.185725582	0.029318693	0.0345734	**0.029318693**
	8	7.995241156	0.830631912	0.267385126	0.057184446	0.0456228	**0.045492**
	10	7.71101	2.91807	0.39916	0.07954	0.079229	**0.073723384**

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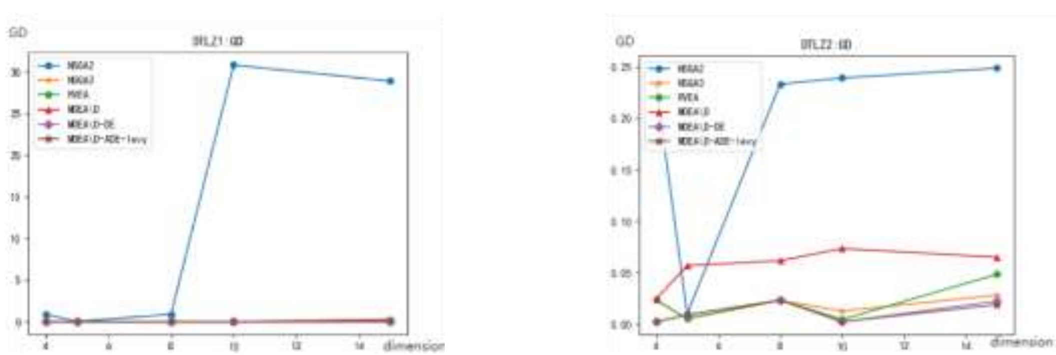
		6756	0177	169	1	5	
	15	7.305457741	3.748682153	0.585633412	0.22727139	0.777328	**0.21854**
DTLZ7	4	1.598779534	1.286912785	1.2370593	1.717198674	**0.380172**	0.519064
	5	0.432928337	0.362390055	0.487894845	0.595173298	2.12323	**0.595173298**
	8	1.598779534	1.286912785	**1.2370593**	1.717198674	2.08856	1.79373
	10	2.97087027	**1.52452207**	1.828440398	2.050215314	1.98769	1.9425
	15	2.9709	**1.5245**	1.8284	2.0502	2.0642	2.0502

In the Table V, when the test functions are DTLZ1, DTLZ5 and DTLZ6, MOEA/D-ADE-levy has the smallest IGD value in each dimension, indicating that its diversity is the best; when the test functions are DTLZ2 and DTLZ3, the algorithms are respectively Obtain sub-optimal values in 5 and 10 dimensions, and have the smallest IGD values in other dimensions; when the test function is DTLZ4, obtain sub-optimal IGD values in 5, 10, and 15 dimensions, and obtain the optimal value in 8 dimensions; When the test function is DTLZ7, the algorithm only performs best in 4 dimensions, and its performance is slightly worse. In the comparison of 35 data items, the algorithm has 25 items as the best value and 6 items as the second best value.

In order to compare the performance of each algorithm more intuitively, compare the NSGA2, NSGA3, and RVEA algorithms with R2-MOEA\D in 4, 5, 8, 10, 15 dimensions, and the test function is DTLZ [1-7]. The GD value comparison is shown in the Figure3:



(a) (b)

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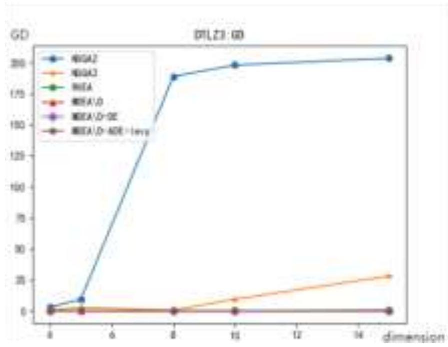
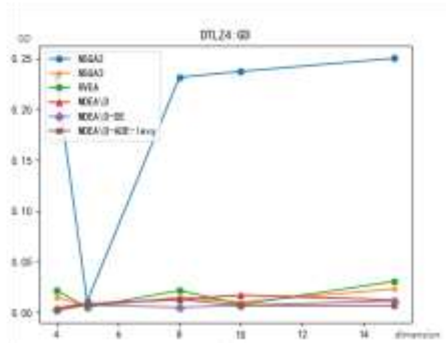
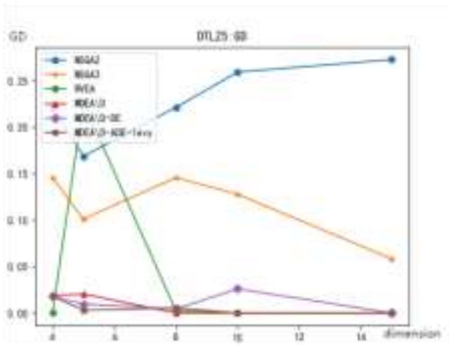


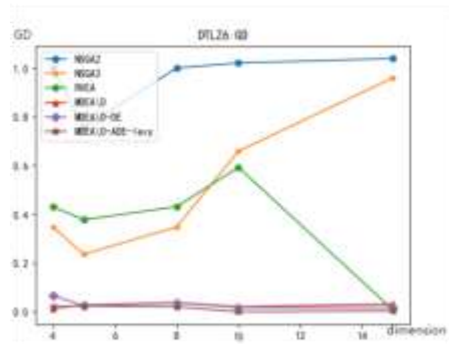
(c)



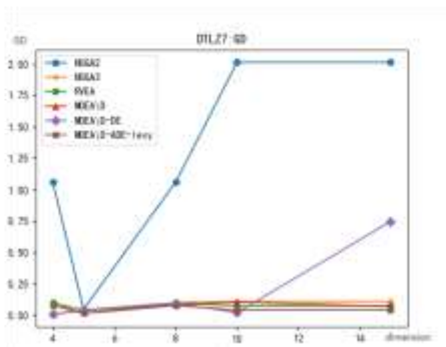
(d)



(e)



(f)



(g)

Fig 3: GD change diagram

It can be seen from the figure that the GD value of MOEA/D-ADE-levy algorithm grows slowly on DTLZ1, 2, 3, 4, 5, 6, 7, and all of them can get smaller GD values. Among them, the others The GD value of the algorithm increases and fluctuates greatly in different test functions. The NSGA2 algorithm has the fastest increase in the GD value in DTLZ [1-7], and its performance is poor. NSGA3 and RVEA algorithms are in the test function DTLZ [5, 6]. The upper GD value changes quickly, and the performance is poor; when the test function is DTLZ7, the performance of the MOEAD-DE algorithm is slightly worse than that of the MOEA/D-ADE-levy algorithm. The GD value of the MOEA\D algorithm is higher than this algorithm. This algorithm is testing the function DTLZ [1-7], its GD value changes slowly with

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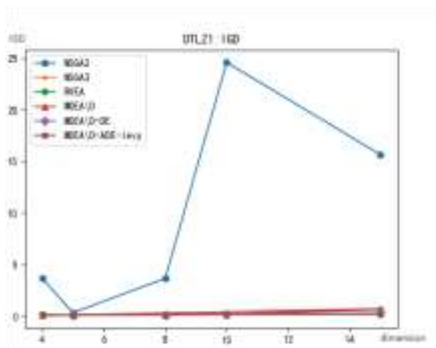
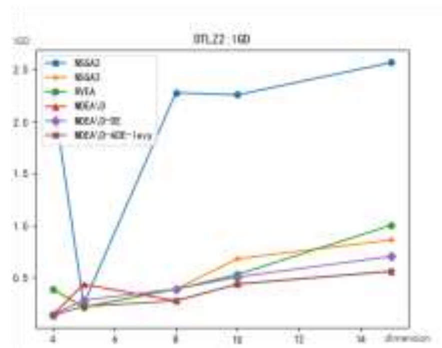
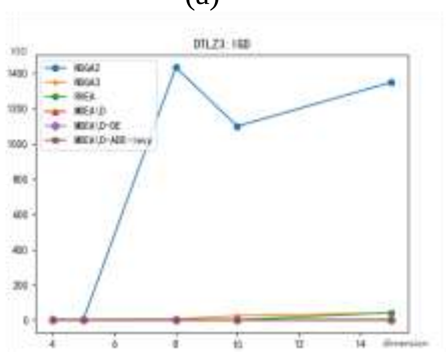
the change of dimensions, and its GD value is lower than the other five algorithms on the same test function in the same dimension, that is, the convergence performance of the MOEA/D-ADE-levy algorithm is excellent for the other five algorithms.



(a)



(b)



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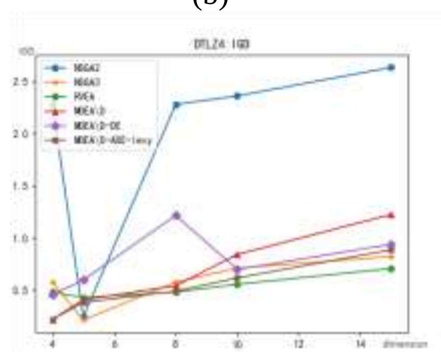

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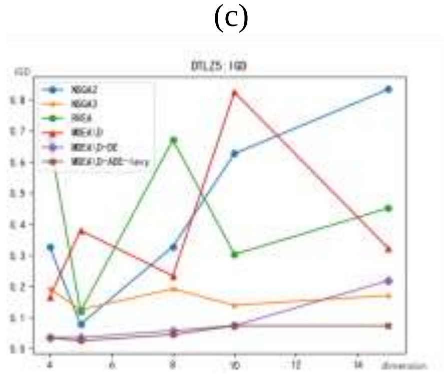

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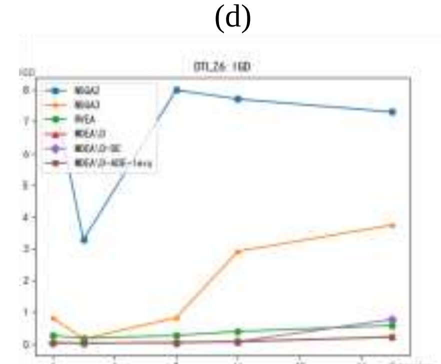

(f)

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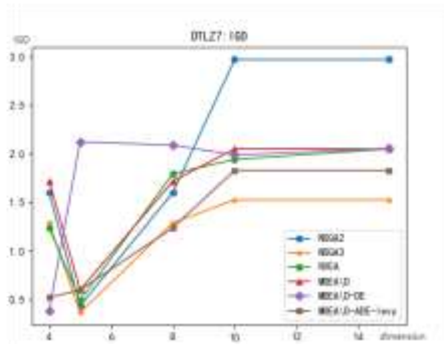

(g)

Fig 4: IGD change diagram

It can be seen from the Figure 4 that the IGD value of the MOEA/D-ADE-levy algorithm increases slowly on DTLZ [1-6], while the GD value of other algorithms increases and fluctuates greatly in different test functions. NSGA2 algorithm in DTLZ [1-7], its IGD value increases the fastest, the performance is poor, N other several algorithms in the test function DTLZ [4-7], its IGD value fluctuates greatly, the performance is poor, The performance of this algorithm is slightly worse when the test function is DTLZ7. The IGD value of this algorithm on the test function DTLZ [1-6] changes slowly with the change of the dimension, and its IGD value is lower than the other five algorithms on the same test function in the same dimension, that is, MOEA/D-ADE- The convergence performance of levy algorithm is better than the other five algorithms.

IV. CONCLUSION

Aiming at the problem that the traditional MOEA\D algorithm has convergence and diversity imbalance, and is easy to fall into the local optimum in the later stage of the algorithm, this paper proposes a MOEA/D-ADE-levy algorithm, which first passes through the orthogonal horizontal mixing matrix And improved Chebyshev's weight vector and initial population with uniform and distribution. For convergence and diversity imbalance, an adaptive selection DE evolution operator is proposed to divide the population into excellent individuals, intermediate individuals and poor individuals. The three individuals select different DE evolution operators, and finally add levy random perturbation to the population falling into the local optimum to increase its global search ability and make the current population jump out of the local optimum. Through this algorithm, we can get:

1. Compare the convergence and diversity of the MOEA/D-ADE-levy algorithm with the NSGA2, NSGA3, RVEA, MOEA\D, MOEA\D-DE algorithm on the test function DTLZ [1-7], MOEA/ Compared with other algorithms in the same dimension, D-ADE-levy algorithm has

smaller GD and IGD values, which shows that the convergence and diversity of this algorithm are better than other algorithms.

2. The MOEA/D-ADE-levy algorithm divides the population into different individual adaptive selection operators, which improves the balance of algorithm convergence and diversity. The addition of levy disturbance in the later stage of the algorithm can make the algorithm jump out of the local optimum.

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REFERENCES

[1] Liu B, Zhang C R, Sun C, et al. The Application of Multi-population Genetic Algorithm in Secondary Air Temperature of Grate Cooler. Acta Metrology, 2019, 40(002): 252-258.

[2] Zheng J H, Dong N J, Ruan G, et al. High-dimensional Multi-objective Optimization Strategy Based on Decision Space Oriented Search. Journal of Software, 2019, 030(009): 2686-2704.

[3] Yu G, Jin Y, Olhofer M. An a priori knee identification multi-objective evolutionary algorithm based on α –dominance. the Genetic and Evolutionary Computation Conference Companion. 2019.

[4] Laumanns M, Zenklusen R. Stochastic convergence of random search methods to fixed size Pareto front approximations. European Journal of Operational Research, 2011, 213(2).

[5] Hughes E J. MSOPS-II: A general-purpose Many-Objective optimizer. IEEE Congress on Evolutionary Computation. IEEE, 2007.

[6] Ishibuchi H, Akedo N, Nojima Y. Relation between Neighborhood Size and MOEA/D Performance on Many-Objective Problems. International Conference on Evolutionary Multi-Criterion Optimization. Springer Berlin Heidelberg, 2013.

[7] Chen F, Zhou J, Wang C, et al. A modified gravitational search algorithm based on a non-dominated sorting genetic approach for hydro-thermal-wind economic emission dispatching. Energy, 2017, 121(FEB.15): 276-291.

[8] Kumar M, Guria C. The elitist non-dominated sorting genetic algorithm with inheritance (i-NSGA-II) and its jumping gene adaptations for multi-objective optimization. Information Sciences, 2017, 382-383:

[9] Deb K, Sundar J. Reference Point Based Multi-Objective Optimization Using Evolutionary Algorithms. Genetic and Evolutionary Computation Conference, GECCO 2006, Proceedings, Seattle, Washington, USA, July 8-12, 2006. 2006.

[10] Xue Y, Zhong J, Tan T H, et al. IBED: Combining IBEA and DE for optimal feature selection in software product line engineering. Applied Soft Computing, 2016:S1568494616303751.

Forest Chemicals Revew
www.forestchemicalsreview.com
ISSN: 1520-0191
July-August 2021 Page No. 1214-1237
Article History: Received: 12 May 2021 Revised: 25 June 2021 Accepted: 22 July 2021 Publication: 31 August 2021

[11] Zhang B, Gan Z C, Chen Y. Topology Optimization of Tactical Communication Network with SMS-EMOA Algorithm. 2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC). IEEE, 2019.
[12] Reddy S R, Dulikravich G S. Many-objective differential evolution optimization based on reference points: NSDE-R. Structural and Multidisciplinary Optimization, 2019(1).
[13] Brockhoff D, Zitzler E. Improving hypervolume-based multiobjective evolutionary algorithms by using objective reduction methods. IEEE Congress on Evolutionary Computation. IEEE, 2007.
[14] Duan Z, Guo Y, Chen Q, et al. A High Dimensional Multi-objective Optimization of Attitude Maneuver Control for Flexible Spacecraft. Information and Control, 2013, 42(3): 299-307.
[15] Tanabe R, Ishibuchi H. Review and analysis of three components of the differential evolution mutation operator in MOEA/D-DE. Soft Computing, 2019.
[16] Zhou Z, Liu X, Xiao H, et al. A DEA-based MOEA/D algorithm for portfolio optimization. Cluster Computing, 2018.
[17] Martinez S Z, Coello C A C. A Proposal to Hybridize Multi-Objective Evolutionary Algorithms with Non-gradient Mathematical Programming Techniques. 10th International Conference on Parallel Problem Solving from Nature (PPSN 2008): 837-846.
[18] Zheng W, Tan Y, Meng L, et al. An improved MOEA/D design for many-objective optimization problems. Appl Intell, 2018, 48, 3839–3861.
[19] Xie C W, Yu W W, Hui Y Z, et al. A high-dimensional multi-objective evolutionary algorithm based on decomposition and collaboration. Journal of Software, 2020, 031(002): 356-373.
[20] Shen X, Zou D X, Zhang Q. Adaptive differential evolution algorithm using double mutation strategy and its application. Computer Engineering and Applications, 2020, v.56; No. 947(04): 151-162.
[21] Chen F, Zhou J Z, Wang C, et al. A modified gravitational search algorithm based on a non-dominated sorting genetic approach for hydro-thermal-wind economic emission dispatching. Elsevier Journal, 2017, 121(C): 276-291.
[22] Cheng R, Jin Y, Olhofer M, et al. A Reference Vector Guided Evolutionary Algorithm for Many-Objective Optimization. IEEE Transactions on Evolutionary Computation, 2016, 20(5).