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# Decomposition Multi-Objective Evolutionary Algorithm Based on Adaptive Neighborhood Adjustment Strategy

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**ABSTRACT** The multi-objective evolutionary algorithm based on decomposition (MOEA/D) uses a fixed neighborhood size and allocates the same algorithm resources for all sub-problems. This approach makes it harder to effectively optimize the sub-problems in different periods of time, slows the convergence of the algorithm and reduces the quality of the decomposition. This paper proposes an adaptive neighborhood adjustment strategy designed to solve this problem. The neighborhood size of each generation of different subproblems can be adjusted adaptively, and limited algorithm resources can be allocated more efficiently to balance the convergence and diversity of the algorithm. In the algorithm performance comparison experiment, this paper compares the proposed algorithm with the MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN in ZDT and DTLZ series test problems. The experimental results show that the proposed algorithm can efficiently allocate limited algorithm resources, improve algorithm convergence, and achieve better overall performance of the decomposition set.

**INDEX TERMS** Multiobjective optimization, evolutionary algorithms, adaptive, neighborhood adjustment.

## I. INTRODUCTION

Many multi-objective optimization problems (MOPs) exist in scientific research and engineering practice. These problems are composed of multiple conflicting objectives such that multiple objectives can reach the optimal solution to the extent possible. Currently, the main method used to solve MOPs is multi-objective evolutionary algorithms (MOEAs) [1].

According to the selection principle of the algorithms, MOEAs can be divided into 1) MOEAs based on Pareto domination [2]–[4], 2) MOEAs based on indicators [5]–[7], 3) MOEAs based on decomposition [8], [9], and 4) MOEAs based on preference [10], [11].

Most of the early multi-objective evolutionary algorithms are based on Pareto dominance, and scholars have done a lot of research on this basis. Gong *et al.* proposed a set-based

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genetic algorithm (SetGA), which modified the fast non-dominance sorting approach of NSGA-II, and proposed a set-based Pareto dominance relation to solve the optimization problem with three or more objectives and at least one objective affected by uncertain factors [12]. Liu *et al.* Proposed a many-objective evolutionary algorithm (1by1IEA) using a one-to-one selection strategy, which selects offspring by calculating the efficiency of convergence indicators, increases the pressure on population selection, and maintains population diversity through niche technologies [13].

With increasing objective dimension, the population size covering the Pareto Front (PF) in the evolutionary algorithm based on Pareto dominance relationship increases exponentially and the proportion of non dominated solutions in the population increases rapidly, resulting in the sharp decline of the search ability of the algorithm, or even stagnation [14]. Zhang *et al.* put forward a multiobjective evolutionary algorithm based on decomposition (MOEA/D) in 2007 [8]. MOEA/D uses aggregation function to decompose

multi-objective problems into several simple subproblems and to coevolve instead of relying on Pareto domination. Compared with the original evolutionary algorithm based on Pareto dominance, MOEA/D reduces the computational complexity and improves the convergence of the algorithm.

In recent years, many scholars have done lots of research work in improving the performance of MOEA/D. Among them, there are two kinds of methods to optimize the allocation of computing resources. The first species is the improvement of weight vector adjustment strategy. It mainly includes: Qi *et al.* proposed a MOEA/D with adaptive weight adjustment(MOEA/D-AWA) [15], introduced a new method to initialize weight vector and adjust weight vector. Chen *et al.* proposed the reference vector guided evolutionary algorithm (RVEA) [9], and adjusted the distribution of weight vectors in the target space through the endpoints of the current Pareto solution set regularly. The second species is the optimization strategy of sub-problems. It mainly includes: Huili *et al.* proposed a MOEA/D based on differential evolution(MOEA/D-DE) [16], introducing differential evolution operator and polynomial mutation to generate offspring. Li *et al.* proposed a stable matching-based selection in MOEA/D (MOEA/D-STM) [17]. It uses a stable matching model to coordinate the selection process in MOEA/D and assigns a solution to each subproblem to balance the convergence and diversity. In order to better solve MOPs with complex Pareto front, Wang *et al.* proposed a replacement strategy for balancing convergence and diversity in MOEA/D(MOEA/D-GR) [18], which gave a global replacement strategy. Yuan *et al.* proposed a balancing convergence and diversity in MOEA/D (MOEA/D-DU) [19]. It uses the improved Tchebycheff function and the vertical distance from the solution to the weight vector to balance convergence and diversity. Zhang *et al.* proposed a dynamic resource allocation decomposition multi-objective evolutionary algorithm (MOEA/D-DRA) [20] for the computing resource allocation problem of different sub-problem. It defines and calculates the utility function value for each sub-problem. The larger the utility function value, the greater the probability that the individual will be selected to participate in evolution. Zhao *et al.* proposed a MOEA/D With an ensemble of neighborhood sizes(ENS-MOEA/D) [21] by analyzing the influence of different size neighborhood on the algorithm. Zhou *et al.* proposed MOEA/D based on dynamic neighborhood adjustment strategy(MOEA/D-DNS) [22] by reducing the neighborhood of boundary sub-problems and subproblems close to the boundary and increasing the neighborhood of other sub-problems. Wu *et al.* proposed MOEA/D based on differentiated neighborhood strategy(MOEA/D-DN) [23] by analyzing different algorithm resources needed by different subproblems.

Through the analysis of the above research, it is found that: a) the difficulty in optimization of different sub-problems varies [10], [20]. As the target dimension increases, assigning the same neighborhood size to each sub-question results in an excess of computational resources for suboptimal

problems and insufficient computational resources for suboptimal problems; b) the increasing objective dimension makes the search ability of the algorithm sharply decrease, and it is difficult to balance the convergence and diversity of the algorithm [24], [25]. To solve the above problems, we propose a decomposition multi-objective evolutionary algorithm based on the adaptive neighborhood adjustment strategy (MOEA/D-ANA). The neighborhood size of the same subproblem in different evolutionary generations is adjusted by the differentiated parameter  $\beta$ . The neighborhood size of different subproblems in the same evolutionary generation is adjusted via the angle  $\theta$ . Thus, limited algorithm resources can be allocated reasonably, and the conflict between the convergence and diversity of the algorithm can be balanced.

## II. BACKGROUND

### A. MOP

The general form of the multi-objective optimization problem is given as follows:

$$\min f(x) = (f_1(x), f_2(x), \dots, f_m(x))^T \quad (1)$$

$$\text{subject to } x \in \Omega \subseteq R^n \quad (2)$$

where  $x = ((x_1, x_2, \dots, x_n))^T$  is an n-dimensional decision vector in decision space  $\Omega$ ;  $f : \Omega \rightarrow \Theta \subseteq R^m$  is an m-dimensional goal vector.

### B. MOEA/D

The core of MOEA/D is decomposition of a complex multi-objective problem into a certain number of single-objective subproblems through an aggregation function and subsequent optimization of all subproblems at the same time. This decomposition method can effectively reduce the complexity and improve the convergence of the algorithm while maintaining the solution set.

Three types of aggregate functions of the MOEA/D are available: weighted sum (WS), Tchebycheff (TCH) and penalty-based boundary intersection (PBI) [9]. In this paper, the subproblems are defined on the Tchebycheff decomposition method as follows:

$$\begin{cases} \min g(x|\lambda, z^*) = \max_{1 \leq i \leq m} \{\lambda_i |f_i(x) - z_i^*|\} \\ \text{subject to } x \in \Omega \end{cases} \quad (3)$$

where  $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_k)$  is the weight vector of the current subproblem,  $z^*$  is the reference point, and  $z^* = \min \{f_i | x \in X\}$ , for each  $i = 1, 2, \dots, k$ .

If the decision maker does not supply the corresponding preference information, the desired solution is evenly distributed on the PF. Therefore, MOEA/D generates a weight vector via the single grid point method, which meets the following conditions:

$$\lambda_1 + \lambda_2 + \dots + \lambda_k = 1 \quad (4)$$

$$\lambda_i \in \left\{ 0, \frac{1}{H}, \frac{2}{H}, \dots, \frac{H}{H} \right\}, \quad i = 1, 2, \dots, k \quad (5)$$

where  $H$  is a user-defined positive integer. The weight vector is uniformly selected on the  $f_1 + f_2 + \dots + f_k = 1$  plane

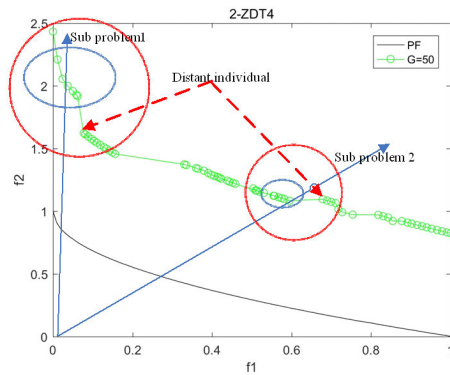


FIGURE 1. Defects of fixed neighborhood.

of  $f_1^2 + f_2^2 + \dots + f_k^2 = 1$  hyperplane, and the number of points meets  $N = C_{H+k-1}^{k-1}$ , where  $k$  is the target number.

### III. DECOMPOSITION MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM BASED ON ADAPTIVE NEIGHBORHOOD ADJUSTMENT STRATEGY

#### A. NEIGHBORHOOD ADJUSTMENT STRATEGY

In MOEA/D, the neighborhood of each subproblem consists of the information of several weight vectors near it. The initialization population  $\{x^1, x^2, \dots, x^N\}$  is generated by the random method, which makes the population distribution in the target space irregular. MOEA/D assigns the same neighborhood size to optimize all subproblems, creating difficulty in full use of the limited algorithm resources, as shown in Figure 1.

Figure 1 shows the Pareto front (PF) graph of MOEA/D on the 2-objective ZDT4 problem when the population evolves to 50 generations. The individual distribution of the population in the target space is highly nonuniform. The blue circles represent the individuals covered by the neighborhood of the current subproblem in MOEA/D, and the red circles represent the individuals covered by the neighborhood of the current subproblem after using the ANA strategy.

It can be seen from Figure 1 that the number of Pareto optimal solutions in the region of subproblem 1 is far from that in the region of subproblem 2. For the former, the size of neighborhood should be reduced appropriately, that is, unnecessary computing resources should be reduced. And for the latter, the neighborhood norm should be increased appropriately, so that the corresponding subproblem has enough algorithm resources to find the optimal solution. However, in the early stage of the algorithm, if the neighborhood is too small (blue circle), sub problem 1 can only be crossed in the limited parent generation. After several generations of cross mutation, most of the new solutions will be similar, which leads to the algorithm falling into local optimization. And if the neighborhood is too large, when the population updates the sub problem, it will produce too many copies, which increases the computational complexity of the algorithm.

In order to avoid losing the excellent solution and falling into the local optimum in the early stage of the algorithm, it is

necessary to increase the size of the neighborhood appropriately, let the distant individuals participate in the propagation of subproblem 1 and subproblem 2, maintain the population diversity and make it approach the Pareto front rapidly. With the algorithm running, the neighborhood assigned to the subproblem is constantly adjusted according to the difficulty of the subproblem optimization.

To solve the problem that the subproblem needs different neighborhood sizes in different evolutionary generation, this paper proposes a neighborhood adjustment strategy (NA). In the early, the strategy maintains the diversity of the population through a large neighborhood scale to avoid the loss of excellent solutions. In the middle and late stage, the diversity of the population has basically been consistent with the PF. The strategy allocates a smaller neighborhood scale for each generation of the subproblem, which can avoid the waste of algorithm resources. As shown in Figure 2.

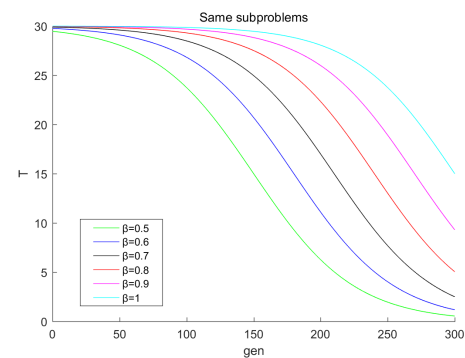


FIGURE 2. NA strategy.

Figure 2 shows the change trend of the neighborhood on the ZDT4 test function when the difference parameter  $\beta$  is set to 0.5, 0.6, 0.7, 0.8, 0.9 and 1 to select the appropriate  $\beta$  value, and the neighborhood cannot be 0.

$$T_i = T_{max} - T_{max} \times \frac{1}{1 + e^{(-8 \times (\frac{gen}{Maxgen}) - \beta)}} \quad (6)$$

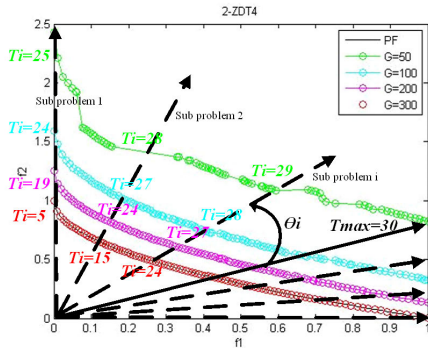
In the NA strategy, with continuous evolution of the population, the neighborhood scale of all subproblems is adjusted by equation (6). This equation is based on the reference [26]. And  $\beta$  is the differentiated parameter. In this paper, we propose a MOEA/D based on the neighborhood adjustment strategy. See Algorithm 1.

#### B. DIFFERENTIATED NEIGHBORHOOD STRATEGY

Wu Feng *et al.* proposed a MOEA/D based differentiated neighborhood strategy [23] and found that the optimization difficulty of different subproblems varied in the same stage. The same neighborhood size cannot make every subproblem obtain the optimal solution. This approach used the differentiated neighborhood strategy to increase the computing resources for the difficult subproblems and reduce the computing resources for the easy subproblems.

**Algorithm 1** Neighborhood-Adjustment

**Input:** the maximal number of neighborhood size  $T_{max}$ ; A set of uniform reference vectors  $W \leftarrow \{\lambda^1, \lambda^2, \dots, \lambda^N\}$ ; the differentiated parameter  $\beta$ ;  
**Output:**  $T = \{T_1, T_2, \dots, T_N\}$ ;  
**for** gen = 1 to Maxgen **do**  
 $T_i = T_{max} - T_{max} \times \frac{1}{1 + e^{(-8 \times (\frac{gen}{Maxgen}) - \beta)}}$  ;  
 $T = \text{ceil}(T_i)$ ;  
**end for**



**FIGURE 3.** Schematic diagram of ANA strategy.

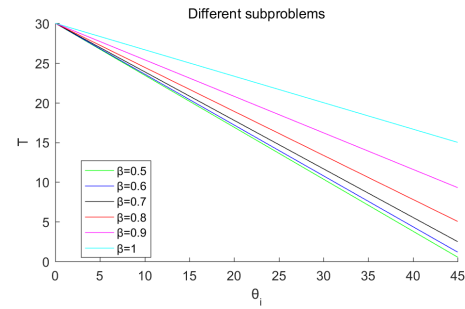
However, the differentiated neighborhood strategy (DN) has the following shortcomings:

1) The DN strategy still adopts a fixed domain scale. Before the algorithm is run, different sizes of neighborhood are configured for different subproblems. The optimal neighborhood scale required for the same subproblem in different periods of algorithm operation is not considered.

2) DN strategy is greatly affected by the parameters  $T_{max}$  and  $T_{min}$ . The optimal domain scale of different objective functions is different, i.e., different parameters  $T_{max}$  and  $T_{min}$  are needed, and these two parameters are pre-tested. Therefore, before application of this strategy, it is necessary to test the applicable parameters  $T_{max}$  in advance for the objective function.

**C. ADAPTIVE NEIGHBORHOOD ADJUSTMENT STRATEGY**

Based on a) the same sub-problem at different times, the required optimal neighborhood size is different (the NA strategy proposed in this paper), and b) for different sub-problems in the same period, the required neighborhood size is different (the DN strategy proposed by Wu Feng et al [23]). IDue to the difficulty in optimizing the different sub-problems in different periods and the difficulty of the required neighborhood size, adaptive neighborhood adjustment (ANA) is further proposed. The strategy adjusts the neighborhood size of the same sub-problem in different periods via the differentiated parameter  $\beta$  and adjusts the neighborhood size of each sub-problem in the same period by the angle  $\theta$ , thereby dynamically adjusting the size of each neighbor of the different sub-problems, as illustrated in Figure 3:



**FIGURE 4.** Influence of differentiated parameter  $\beta$  on the neighborhood of subproblems when  $G = 300$  under ANA strategy.

To show the effect of ANA more intuitively, this paper takes the population evolution  $g = 50, 100, 200,$  and  $300$  as an example on the 2D ZDT4 problem (as shown in Figure 3). From the vertical perspective, in the early stage of the algorithm, the neighborhood size of each subproblem changes to a small extent. When the population evolves to the 2/3 stage, the neighborhood size of each subproblem is appropriately reduced. For the easy subproblem 1, the neighborhood size is rapidly reduced from 30 to 5. For the difficult subproblem 2 and subproblem I, the change in the neighborhood size is small. From a horizontal perspective, in the early stage of the algorithm, to ensure that the population diversity and the optimization difficulty of different subproblems is different, this approach adjusts the neighborhood size of different subproblems in the same period according to the angle  $\theta_i$  between the weight vector bound by individuals and the center weight vector [17].

$$T_i = T_{max} - T_{max} \times \frac{1}{1 + e^{(-8 \times (\frac{gen}{Maxgen}) - \beta)}} * \frac{\theta_i}{\theta_{max}} \quad (7)$$

In summary, in the ANA strategy, we use equation (7) to adjust the neighborhood size of each generation. This equation is based on the reference [26]. Therefore, the variation degree of the neighborhood scale of the same subproblem in different periods is regulated by the differentiated parameter  $\beta$  (Figure 2), and the neighborhood scale of different subproblems in the same period is adjusted by the angle  $\theta_i$  between the weight vector of different subproblems and the center vector (Figure 4). This strategy is presented in detail in Algorithm 2.

**Algorithm 2** Adaptive-Neighborhood-Adjustment

**Input:** the maximal number of neighborhood size  $T_{max}$ ; A set of uniform reference vectors  $W \leftarrow \{\lambda_1, \lambda_2, \dots, \lambda_N\}$ ; the difference parameter  $\beta$ ;  
**Output:**  $T = \{T_1, T_2, \dots, T_N\}$ ;  
**for** gen = 1 to Maxgen **do**  
 $T_i = T_{max} - T_{max} \times \frac{1}{1 + e^{(-8 \times (\frac{gen}{Maxgen}) - \beta)}} * \frac{\theta_i}{\theta_{max}}$  ;  
 $T = \text{ceil}(T_i)$ ;  
**end for**

In this paper, we use IGD as an analysis standard for the influence of different neighborhood sizes on the optimization

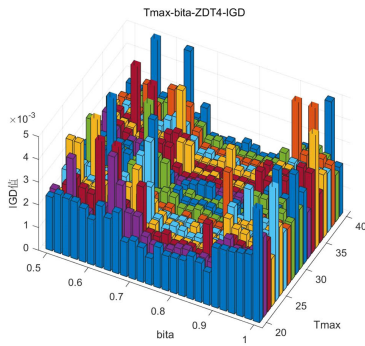


FIGURE 5. Test chart of parameters  $T_{max}$  and  $\beta$ .

difficulty of different subproblems in different stages. We confirm that the two parameters  $T_{max}$  and  $\beta$  of  $T_i$  are adjusted in ANA strategy. where  $T_{max}$  is the upper limit of  $T_i$ , and  $\beta$  determines the degree of change of  $T_i$  in search process.

To find the suitable  $T_{max}$  and parameters  $\beta$ , this paper takes the ZDT4 problem as an example, and the maximum evolution generation is  $gen - max = 300$ . We test the IGD value obtained by MOEA/D-ANA under the different parameters  $T_{max}$  and  $\beta$  (where  $T_{max} \in [20, 40]$ ,  $\beta \in [0.5, 1]$ ). The test results are shown in Figure 5.

Figure 5 shows the change of IGD value with  $\beta$  value obtained by the algorithm when  $T_{max}$  value is the same. In order to better visualize the influence of different  $T_{max}$  and  $\beta$  on algorithm performance, the picture sets different colors for adjacent  $T_{max}$ . It can be seen directly when the differentiated parameter  $\beta \in [0.72, 0.86]$ , the algorithm performance tends to be stable, and the IGD values are less than  $2E-03$ . This result indicates that the performance of ANA is better under the parameter combination at this time. When the  $T_{max}$  axis remains unchanged and the differentiated parameter  $\beta$  gradually increases, the change degree of the neighborhood size of the subproblem gradually decreases in the algorithm searching process, as shown in Figure 2. The change trend of each column of bars is decreasing-stationary-increasing. This result shows that the size of the neighborhood is too large or the neighborhood is too small, which partially affects the convergence performance of the algorithm. When  $\beta \in [0.7, 0.9]$ , the performance of the algorithm is stable. When  $T_{max}$  increases, the resources obtained by the subproblem in the algorithm search process gradually increase. At this time, the change trend of each column of bars is decreasing-stationary, such as  $T_{max} \in [20, 40]$ ,  $\beta = 0.8$ . It shows that when the neighborhood is too small, due to the lack of computing resources, the algorithm falls into the local optimum and cannot further approach the ideal Pareto front. The decrease of the cylinder gradually becomes stable, which shows that with the increase of the computing resources of the subproblem, the subproblem gets more excellent solutions to reproduce, so that it can jump out of the local optimum, which is conducive to improving the convergence of the algorithm. But at last, the column rises, which shows that too much computing resources will make the population produce

too many copies when updating sub problems, hinder the evolution of the population, and reduce the quality of solution set.

Thus, for different subproblems in different stages and only in the appropriate neighborhood size, the limited algorithm resources can be maximized to maintain the diversity of the solution set and improve the convergence performance of the algorithm. Therefore, the most suitable control parameters of MOEA/D-ANA are set as  $\beta = 0.82$  and  $T_{max} = 30$ .

#### D. ALGORITHM STEPS

The Tchebycheff function is a common aggregation function method used in the decomposition of MOEAS. To alleviate the difficulty in maintaining the diversity of the algorithm, this paper adopts the improved version of Tchebycheff in MOEA/D-DU [19]:

$$g(x|\lambda, Z^*) = \max_{1 \leq i \leq k} \left\{ \frac{1}{\lambda_i} |f_i(x) - Z_i^*| \right\} \quad (8)$$

where  $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_k)$  is the weight vector of uniform distribution, and  $Z^*$  is the ideal point.

Compared with the original Tchebycheff function, this improved version has two advantages [19]: 1) the uniformly distributed weight vector renders the search direction in the target space uniform, and 2) each weight vector corresponds to the optimal solution on the unique Pareto front (PF). The mathematical proof can be found in reference [11]. The MOEA/D-ANA is shown in Algorithm 3.

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#### Algorithm 3 MOEA/D-ANA

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**Input:** Multi-objective Optimization Problem; Termination condition; Population size; the maximal number of neighborhood size  $T_{max}$ ; A set of uniform reference vectors  $W \leftarrow \{\lambda^1, \lambda^2, \dots, \lambda^N\}$ ; the difference parameter  $\beta$ ;  
**Output:**  $\{x^1, \dots, x^N\}$ ;  $\{f(x^1), \dots, f(x^N)\}$   
 Initial the population:  $P \leftarrow \{x^1, x^2, \dots, x^N\}$ ;  
 Initialization the ideal point:  $Z^* \leftarrow (Z_1, Z_2, \dots, Z_k)^T$ ;  
**for**  $gen = 1$  to  $Maxgen$  **do**  
      $T = Adaptive\text{-}Neighborhood\text{-}Adjustment(\beta, T_{max})$ ;  
     **for**  $i = 1$  to  $N$  **do**  
         **if**  $rand() < \delta$  **then**  
              $B \leftarrow B(i)$ ;  
         **else**  
              $E \leftarrow 1, 2, \dots, N$ ;  
         **end if**  
          $y \leftarrow GenticOperators(x_k, x_l)$ ;  
          $UpdateIdealPoint(y, Z^*)$ ;  
          $UpdateNeigh(y, Z^*, W, B(i), P)$ ;  
     **end for**  
**end for**  
**return** All non-dominated solutions in P

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#### IV. SIMULATION EXPERIMENT AND ANALYSIS

The experimental environment is an Intel(R) Core(TM) i7-4770HQ CPU @2.20 GHz and 16.0 GB. To verify the

performance of MOEA/D-ANA, it is compared with that of the typical algorithms MOEA/D [8], MOEA/D-GR [18], MOEA/D-DU [19], and MOEA/D-DN [23]. To reduce the deviation of the experimental results caused by random factors, each test function was run 20 times independently in this experiment, and its mean value and standard deviation were calculated as the final test results of this experiment. Bold font in Table means that compared with other comparison algorithms, the Algorithm has the best results.

This process selects three indicators to measure the performance of the algorithm in different aspects. Generation distance (GD) [27] is used to measure the convergence of the algorithm, and the smaller the value, the closer the solution set of the algorithm is to PF, indicating better convergence. The uniformity index (SP) [28] is used to measure the uniformity of the solution set distribution, and the smaller the value, the more uniform the distribution, and the better the diversity of the solution set. The inverse generation distance (IGD) [29] is used to measure the overall performance of the algorithm, and the smaller the value, the higher the overall quality of the solution set obtained by the algorithm.

#### A. PARAMETER SETTING

In this work, we consider the 2-objective ZDT problems (ZDT1-4 and ZDT6) [30] as test objects, and the evolutionary generation is set as 300. We select DTLZ problems (DTLZ1-4) [31] with 3-, 4- and 5-objective tests. For the 3- to 5-objective problems, the evolutionary generation of the DTLZ2 and DTLZ4 populations is set to 500. For the 3-objective problems, the maximum evolutionary generation of DTLZ1 and DTLZ3 is set to 1000; for the 4-objective problems, it is set to 2000; and for the 5-objective problems, it is set to 3000. The specific parameter settings are shown in Table 1:

TABLE 1. Parameter settings.

M	H	N
2	99	100
3	13	105
4	7	120
5	5	126

#### B. PERFORMANCE COMPARISON BETWEEN NA STRATEGY AND ANA STRATEGY

The neighborhood size of each comparison algorithm is set as follows: the neighborhood scale of MOEA/D and MOEA/DDU is  $T = 20$ , and the neighborhood scale of MOEA/D-GR is  $T = 10$ . To prove the effectiveness of the ANA strategy, the control variable method is used to set the neighborhood size of the MOEA/D-DN algorithm using the differentiated domain strategy on the DTLZ series functions to set  $T_{max} = 30$  and  $T_{min} = 5$ . The control parameters of MOEA/D-ANA are set as  $\beta = 0.82$  and  $T_i \in [5, 30]$ ,  $\theta_i \in [0^\circ, 45^\circ]$ .

To verify the effectiveness of the NA strategy and ANA strategy proposed in this paper, the GD, SP and IGD indices of MOEA/D-ANA, MOEA/D-NA and MOEA/D on the ZDT problems are tested, and they are measured with respect to the convergence, the uniformity of the solution set distribution and the performance of the algorithm. After each ZDT problems is run 20 times, the mean value and standard deviation of the results are taken as the final test results. And T-test was used to test the significance of the algorithm performance improvement after adopting NA strategy and ANA strategy. Where “+”, “-” and “=” indicate that the measured index value is at a significant level of 5%, MOEA/D-NA is better than, inferior to, or not different from MOEA/D, MOEA/D-ANA is superior, inferior, or not different from MOEA/D-NA. As shown in Table 2.

It can be observed from Table 2 that in the ZDT problems, with use of the NA strategy, the convergence, uniformity and comprehensive performance of the solution set solved by MOEA/D-NA are mostly better than those of MOEA/D. The results show that the optimal neighborhood size of the same subproblem is different in different stages. In the early stage, the larger neighborhood maintains the diversity of the population and avoids loss of the optimal solution. In the later stage, a smaller neighborhood size is allocated to each generation of the subproblem to avoid the waste of algorithm resources and promote the population convergence. This result verifies the effectiveness of the NA strategy. However, the improvement in the algorithm performance is not significant because in the same period, the optimization difficulty of the different subproblems is different, and the same neighborhood scale cannot make each subproblem obtain the optimal solution.

Figure 8 shows the PF obtained by MOEA/D, MOEA/D-NA and MOEA/D-ANA algorithm and the ideal PF on the 2D ZDT test function, so as to directly measure the uniformity of the set distribution solved by the algorithm and the convergence of the algorithm. It can be seen from Figure 8 (d) that at the end of population evolution, MOEA/D-ANA has completely converged to Pareto frontier, while MOEA/D and MOEA/D-NA have fallen into local optimum. From the other four test functions except Figure 8 (d), it can be seen intuitively that at the end of population evolution, although the three algorithms have converged to the front, the convergence effect MOEA/D-ANA is the best, MOEA/D-NA is the second, MOEA/D is the worst.

Therefore, based on the NA strategy, we make further improvements and propose the ANA strategy according to the difficulty of different subproblems. It can be observed from Table 2 that with use of the ANA strategy, the convergence and comprehensive performance of the solution set of the algorithm are not only significantly superior to those of MOEA/D but also strictly superior to those of MOEA/D-NA. The solution set uniformity is mostly weakly superior to those of MOEA/D and MOEA/D-NA. The results show that the ANA strategy can significantly improve the convergence and overall performance of the algorithm by not affecting the diversity of the algorithm.

**TABLE 2.** Comparisons of GD, SP and IGD indices before and after improvement.

Test Function		MOEA/D			MOEA/D-NA			MOEA/D-ANA		
		GD	SP	IGD	GD	SP	IGD	GD	SP	IGD
ZDT1	Mean	6.24E-04	1.02E-02	7.51E-03	5.04E-04	<b>9.82E-02</b>	6.63E-03	<b>8.84E-05</b>	1.00E-02	<b>3.87E-03</b>
	Std	7.44E-05	1.25E-03	6.82E-04	8.66E-05	2.29E-04	6.69E-04	<b>1.75E-06</b>	<b>5.70E-05</b>	<b>7.96E-07</b>
	T-test				+	-	+			
	T-test							+	+	+
ZDT2	Mean	2.54E-04	4.84E-03	4.82E-03	1.53E-04	<b>4.13E-03</b>	4.85E-03	<b>9.51E-05</b>	4.21E-03	<b>3.81E-03</b>
	Std	2.03E-04	1.10E-03	1.32E-03	1.26E-04	7.18E-04	1.06E-03	<b>2.57E-06</b>	<b>8.45E-06</b>	<b>1.12E-05</b>
	T-test				+	+	-			
	T-test							+	-	+
ZDT3	Mean	5.87E-04	2.31E-02	1.16E-02	6.59E-04	2.31E-02	2.96E-03	<b>5.63E-04</b>	<b>2.21E-02</b>	<b>2.91E-03</b>
	Std	1.36E-04	2.40E-03	1.23E-02	2.81E-05	4.41E-04	1.03E-04	<b>4.09E-06</b>	<b>6.47E-05</b>	<b>9.13E-06</b>
	T-test				-	=	+			
	T-test							+	+	+
ZDT4	Mean	2.53E-02	1.67E-02	9.85E-02	1.71E-02	1.25E-02	7.15E-02	<b>3.53E-04</b>	<b>9.97E-03</b>	<b>1.92E-03</b>
	Std	1.50E-02	6.07E-03	6.10E-02	1.42E-02	3.20E-03	6.15E-02	<b>1.67E-04</b>	<b>9.07E-05</b>	<b>5.87E-04</b>
	T-test				+	+	+			
	T-test							+	+	+
ZDT6	Mean	8.87E-04	8.22E-03	2.93E-03	5.34E-04	4.70E-03	<b>2.83E-03</b>	<b>3.49E-04</b>	<b>2.83E-03</b>	2.88E-03
	Std	2.31E-03	2.32E-02	2.50E-04	5.97E-04	6.07E-03	5.92E-05	<b>4.12E-07</b>	<b>6.19E-06</b>	<b>2.57E-06</b>
	T-test				+	+	+			
	T-test							+	+	-

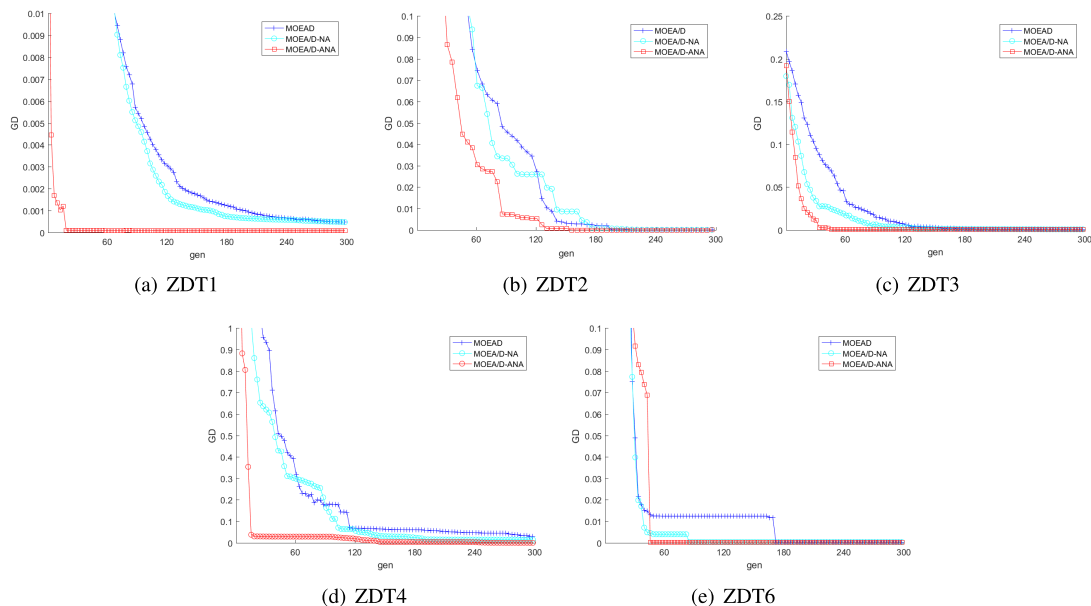
**FIGURE 6.** GD index curve of two strategies on 2D ZDT test function.

Figure 6 shows the change curve of the GD index on the ZDT problems in which the two strategies are used to measure the convergence speed and accuracy of the algorithm. In the early stage of evolution, the GD index curve using the ANA strategy shows a rapid downward trend, thus converging to the PF. MOEA/D and MOEA/D-NA not only converge slowly but also gradually stabilize after 250 generations. On the

ZDT3 problem (discontinuous, multimodal), MOEA/D and MOEA/D-NA waste limited resources in discrete areas.

On the ZDT4 problem (continuous convex, multimode), compared with that of MOEA/D and MOEA/D-NA, the accuracy of the GD value obtained by MOEA/D-ANA is increased by 2 orders of magnitude, and the accuracy of the SP value and IGD value are increased by 1 order of

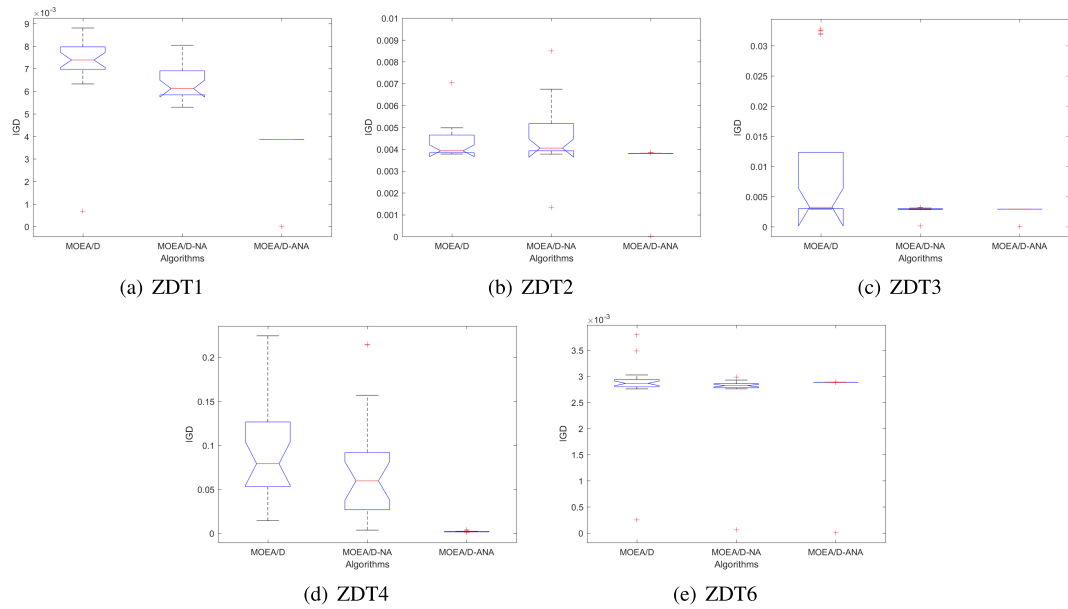


FIGURE 7. IGD box graphs of two strategies on 2D ZDT test functions.

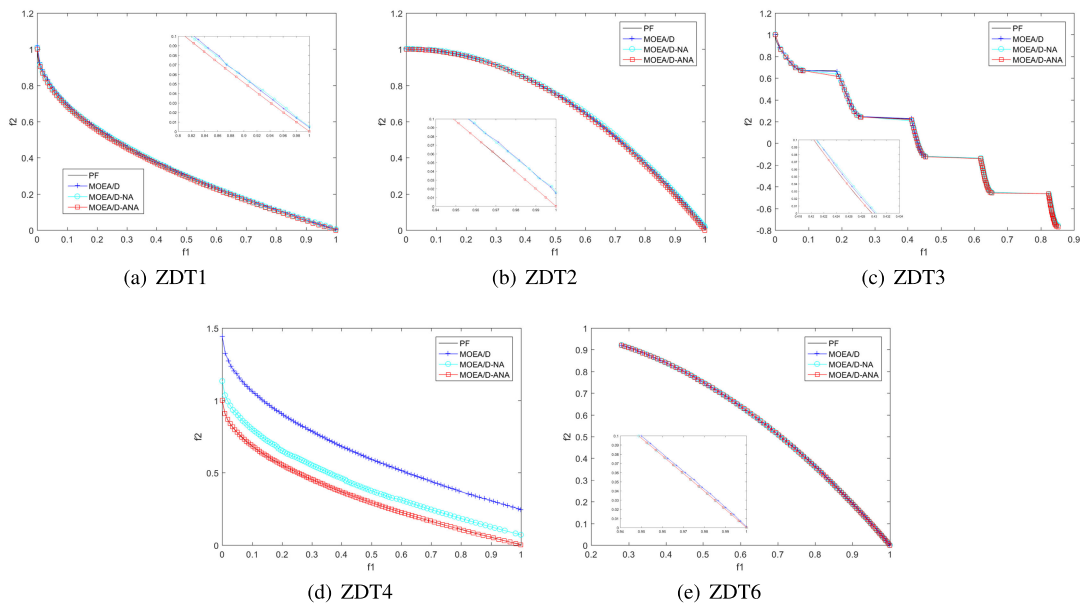


FIGURE 8. Pareto fronts of 3 algorithms on ZDT test functions.

magnitude. Moreover, from Figure 6(d), when the GD index curve of MOEA/D-ANA tends to be stable and convergent after 150 generations, MOEA/D and MOEA/D-NA are still undergoing slow iteration and eventually do not converge. The reason for this result is that in the target space, the initial population of ZDT4 is located far away from the PF, which makes it more difficult for the population to quickly converge to the PF. However, the continuous convex and multimodal function characteristics make it easy for the algorithm to fall into local optima. Moreover, due to the different degree of difficulty in the optimization of different subproblems, the

neighborhood of the same scale cannot ensure that the new solution generated by the population can jump out of the local optimum.

Figure 7 shows the statistical box chart of the IGD index values of the two strategies used on the 2-objective ZDT problem to directly measure the overall quality of the solution set of the algorithm and the stability of the algorithm. We note that the quartile distance of MOEA/D-ANA in the box graph (the shortest box length) is far less than that of MOEA/D and MOEA/D-NA, and the outliers are fewer or even none, which shows that the stability of the MOEA/D-ANA algorithm is



TABLE 3. GD Index test results of 4 algorithms in 3 to 5-objective DTLZ problem.

Test Function M	MOEA/D		MOEA/D-GR		MOEA/D-DU		MOEA/D-DN		MOEA/D-ANA	
	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)
DTLZ1	3	1.04E-03(2.34E-05)	1.16E-02(2.23E-02)	5.11E-03(1.03E-02)	1.10E-03(2.24E-04)	<b>6.54E-04(1.39E-04)</b>				
	4	1.26E-03(1.24E-05)	3.72E-01(3.29E-01)	7.66E-03(2.66E-02)	1.55E-03(3.60E-05)	<b>1.26E-03(2.57E-05)</b>				
	5	2.21E-03(8.70E-06)	3.56E-01(2.81E-01)	3.08E-02(4.49E-02)	2.22E-03(7.79E-06)	<b>3.69E-04(2.62E-04)</b>				
DTLZ2	3	7.08E-04(4.98E-05)	1.14E-03(1.11E-03)	<b>6.28E-04(5.68E-05)</b>	7.21E-04(4.89E-05)	6.80E-04(4.15E-05)				
	4	4.00E-03(6.04E-05)	4.85E-03(1.13E-03)	4.44E-03(6.65E-05)	4.43E-03(5.86E-05)	<b>3.97E-03(6.08E-05)</b>				
	5	7.62E-03(9.64E-05)	2.42E-02(4.31E-03)	3.47E-03(3.09E-04)	7.79E-03(6.33E-05)	<b>3.18E-03(1.72E-04)</b>				
DTLZ3	3	1.08E-01(1.40E-01)	5.03E-01(9.60E-01)	2.07E+00(1.12E+00)	1.66E-01(1.35E-01)	<b>7.57E-02(1.19E-01)</b>				
	4	1.09E-01(1.52E-01)	5.17E+00(2.77E+00)	6.98E-01(3.71E-01)	2.09E-01(1.87E-01)	<b>1.88E-02(4.34E-02)</b>				
	5	8.90E-01(1.40E-01)	3.40E+00(2.91E+00)	6.21E-01(4.94E-01)	8.14E-02(1.21E-01)	<b>8.95E-03(1.92E-02)</b>				
DTLZ4	3	2.74E-03(7.87E-05)	2.91E-03(3.84E-04)	2.09E-03(6.71E-05)	2.79E-03(6.17E-05)	<b>1.54E-03(4.78E-05)</b>				
	4	3.85E-03(6.71E-05)	2.75E-02(1.19E-02)	4.11E-03(6.11E-05)	<b>3.79E-03(7.40E-05)</b>	3.99E-03(9.64E-05)				
	5	6.76E-03(4.46E-04)	2.61E-02(8.84E-03)	4.74E-03(6.59E-04)	6.68E-03(4.46E-04)	<b>4.19E-03(1.87E-04)</b>				

TABLE 4. IGD indicator test results of 4 Algorithms in 3- to 5-objective DTLZ problem.

Test Function M	MOEA/D		MOEA/D-GR		MOEA/D-DU		MOEA/D-DN		MOEA/D-ANA	
	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)	Mean	(Std)
DTLZ1	3	7.42E-02(2.02E-04)	7.41E-02(5.21E-04)	5.69E-02(3.52E-02)	7.52E-02(2.09E-03)	<b>2.01E-02(7.95E-04)</b>				
	4	1.05E-01(1.96E-04)	1.28E-01(4.79E-02)	4.69E-02(1.06E-03)	1.05E-01(1.56E-04)	<b>4.65E-02(6.26E-04)</b>				
	5	1.13E-01(5.53E-05)	1.56E-01(1.34E-01)	2.87E-01(3.38E-01)	1.13E-01(9.87E-05)	<b>6.72E-02(4.75E-04)</b>				
DTLZ2	3	2.71E+00(6.29E-03)	2.72E+00(2.79E-02)	2.07E+00(1.50E-02)	2.72E+00(1.29E-02)	<b>5.24E-02(3.33E-04)</b>				
	4	2.74E-01(1.24E-03)	2.71E-01(1.65E-03)	<b>1.37E-01(1.54E-03)</b>	2.73E-01(1.05E-03)	1.39E-01( <b>1.15E-03</b> )				
	5	3.10E-01(1.32E-03)	3.88E-01(2.44E-02)	<b>2.05E-01(1.67E-03)</b>	3.09E-01(8.81E-04)	2.09E-01(3.35E-03)				
DTLZ3	3	4.27E+00(5.55E+00)	5.10E+00(7.23E+00)	7.54E+01(4.37E+01)	6.28E+00(5.25E+00)	<b>7.60E-01(5.16E-01)</b>				
	4	1.26E+00(1.55E+00)	6.89E+00(9.51E+00)	7.85E+00(4.17E+00)	2.43E+00(2.16E+00)	<b>2.80E-01(4.12E-01)</b>				
	5	1.07E+00(1.35E+00)	4.44E+00(7.19E+00)	5.67E+00(4.37E+00)	9.65E-01(1.11E+00)	<b>2.91E-01(2.14E-01)</b>				
DTLZ4	3	3.00E-01(2.50E-02)	3.04E-01(2.01E-02)	2.61E-01(7.26E-03)	3.11E-01(1.66E-02)	<b>5.91E-02(3.83E-03)</b>				
	4	2.81E-01(8.67E-03)	3.42E-01(3.69E-02)	<b>1.55E-01(7.25E-03)</b>	2.89E-01(8.13E-03)	1.66E-01(9.18E-03)				
	5	3.27E-01(9.93E-03)	4.03E-01(3.49E-02)	<b>2.08E-01(5.29E-03)</b>	3.31E-01(7.65E-03)	2.25E-01(9.40E-03)				

high and that the overall quality of the solution set is better. The median (red line) and maximum value of MOEA/DANA in the box chart are significantly lower than those of the two improved algorithms, which shows that the accuracy and performance of the MOEA/D-ANA algorithm are better.

By applying the ANA strategy to dynamically adjust the size of each generation neighborhood of each subproblem and allocate the algorithm resources effectively, the convergence accuracy and speed of the algorithm can be significantly improved under the premise of maintaining the diversity of the algorithm to avoid the algorithm falling into local optima and improve the overall quality of the solution set of the algorithm. The experiments show the effectiveness of the ANA strategy.

C. ALGORITHM PERFORMANCE COMPARISON

To verify the overall performance of MOEA/D-ANA in the multi-objective optimization problem, GD and IGD are used to measure the convergence and set uniformity of MOEA/D, MOEA/D-GR, MOEA/D-DU, MOEA/D-DN and

MOEA/D-ANA in the 3- to 5-objective optimization problem. To avoid deviation of the result caused by random factors, each test function is run 20 times independently, and its mean value and standard deviation are taken as the final test results.

1) ALGORITHM CONVERGENCE ANALYSIS

Table 3 shows the GD index test results of the 5 algorithms on the 3- to 5-objective DTLZ problem. To more intuitively reflect the convergence of the algorithm, Figure 9 shows the curve of the GD index of the 5 algorithms on the 3- to 5-objective DTLZ problem changing with the evolutionary generation.

From Table 3, we observe that the mean value and standard deviation of the convergence (GD index value) obtained by MOEA/D-ANA are strictly superior to those of the other three comparison algorithms in the 3- to 5-objective DTLZ1 and DTLZ3 problems because the DTLZ1 and DTLZ3 problems are complex multimodal problems, and multiple local optimal solutions exist. This situation makes optimization of

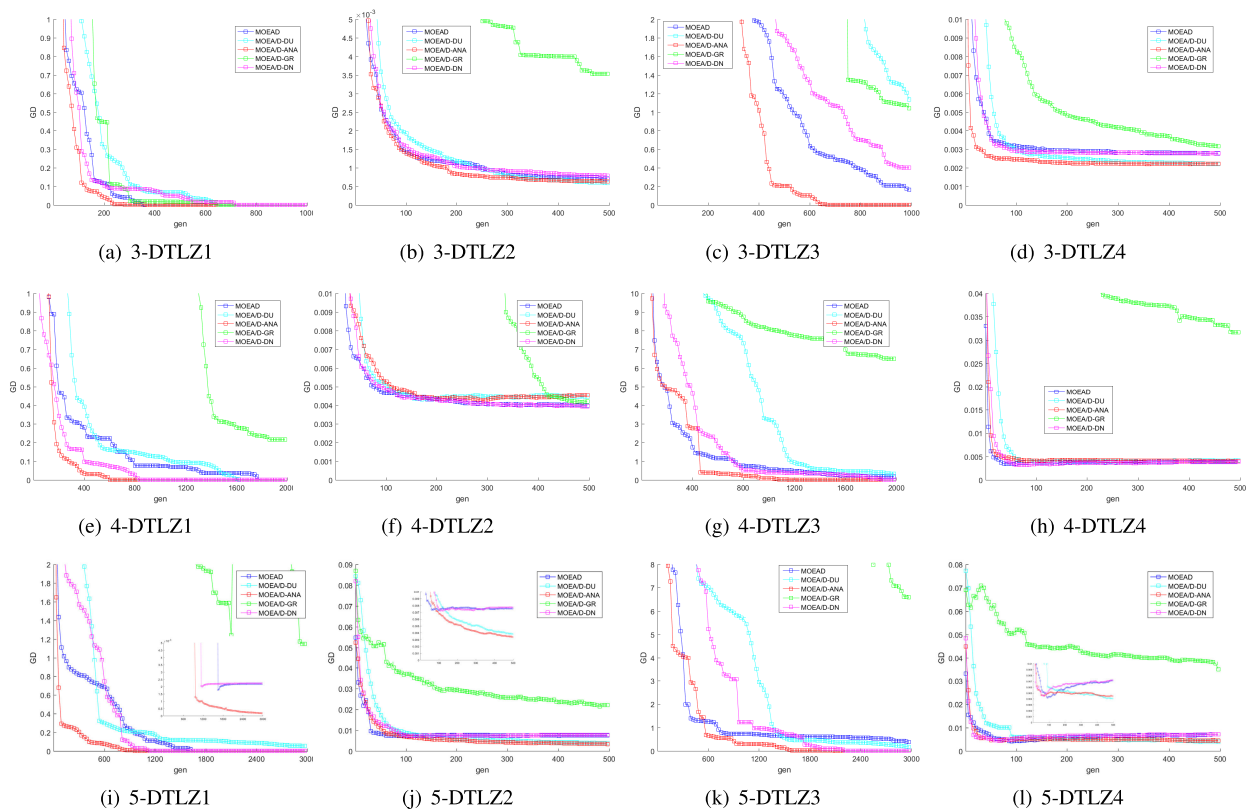


FIGURE 9. GD evolution curve of 4 algorithm on 3 to 5-objective DTLZ problem.

the different subproblems difficult and easy, and the initial population is located far away from the PF in the target space. Therefore, the algorithm requires additional evolutionary generations to converge to the PF. Thus, the ANA strategy can improve the convergence of the algorithm and avoid falling into the local optimum in the process of the algorithm search by reasonably allocating the optimal neighborhood size for different subproblems in different periods.

It can be observed from Figure 9 that for the 3-objective DTLZ3 problem, MOEA/D-ANA must rapidly converge to the Pareto front when the population evolves to 500 generations. However, MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN only converge to the Pareto front when there are 1000 generations, and the final test value is still inferior to that of MOEA/DANA. For the 4-objective DTLZ1 and DTLZ3 problems, MOEA/D-ANA rapidly converges to the PF when they evolve to 1000 generations, whereas MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN need to evolve to at least 1600 generations. For the 5-objective DTLZ1 and 3-objective problems, MOEA/D-ANA can converge to the PF when the population evolves to 2000 generations, whereas the comparison algorithm cannot converge to the PF when the population evolves to the end. This result shows that the objectives are few, the complexity of the algorithm is low, and the population evolves to a certain algebra and that MOEA/D, MOEA/D-GR, MOEA/D-DU

and MOEA/D-DN can all converge to the PF. With the increase in the objective, the complexity of the algorithm also increases. Even if the population has sufficient evolutionary generations, MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN fall into the local optimum and cannot converge to the PF. However, MOEA/D-ANA maximizes the limited algorithm resources through the ANA strategy, which not only makes the population converge to the front faster but also obtains a higher solution set accuracy.

In the 3- to 5-objective DTLZ2 and DTLZ4 problems, MOEA/D-DU and MOEA/D-ANA show little difference, but they are strictly superior to MOEA/D, MOEA/D-GR and MOEA/D-DN, and this advantage is more obvious with increasing dimensions. Because the DTLZ2 and DTLZ4 test functions are simple single-mode problems and the initial population is close to the PF, the population can quickly converge to the PF in the early stage of the algorithm search. The difference between the subproblems is not significant, and thus the improvement effect of the MOEA/D-ANA algorithm is not obvious in the DTLZ1 and DTLZ3 problems.

Horizontally, MOEA/D-ANA improves the convergence of problems with complex Pareto solution sets, such as the DTLZ1 and DTLZ3 test problems. From the vertical point of view, we can obtain the following conclusions: 1) with the increase in the objective, the value of the GD index gradually increases, which shows that the selection pressure

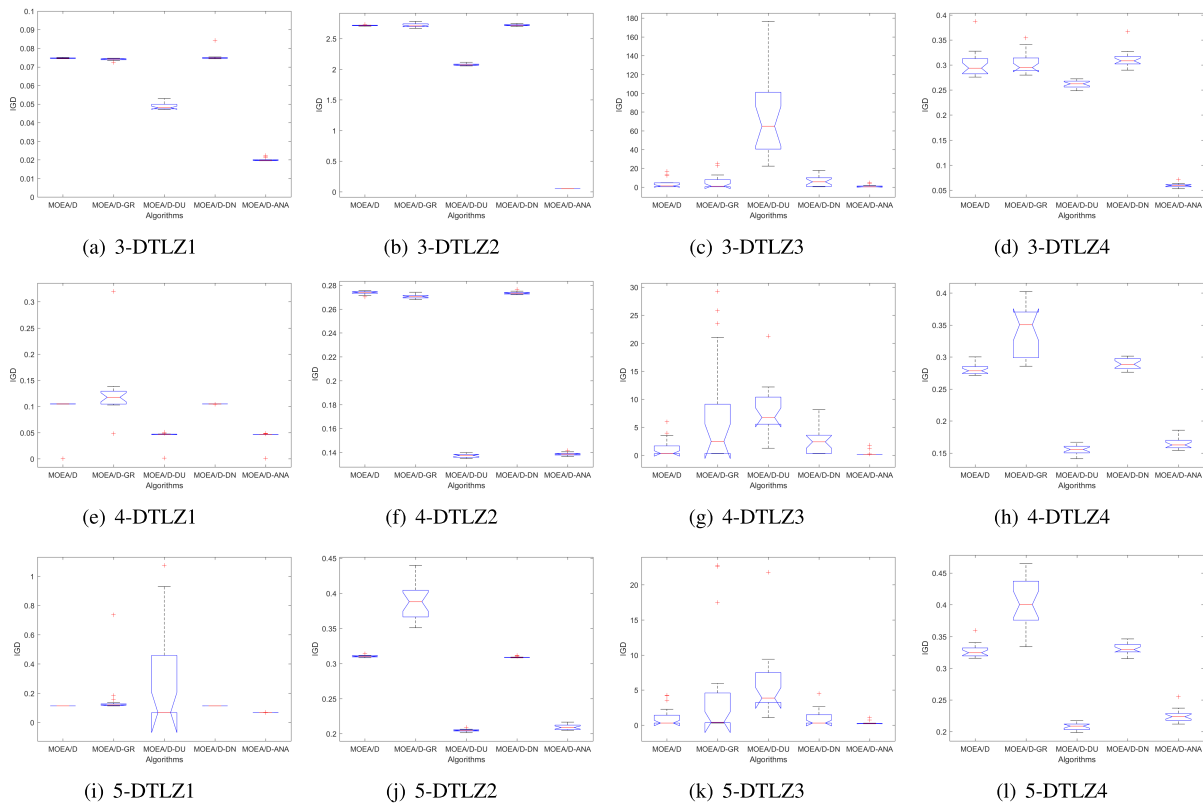


FIGURE 10. IGD box graph of 4 algorithms on 3- to 5-objective DTLZ problem.

of the solution and the complexity of the algorithm increase with the increasing target dimension, leading to a decrease in the convergence of MOEA/D, MOEA/D-GR, MOEA/DDU, MOEA/D-DN and MOEA/D-ANA with the increasing target dimension, and 2) with the increase in the objective, the GD value obtained by MOEA/D-ANA changes minimally, which shows that the ANA strategy can effectively relieve the pressure of solution selection in multi-objective optimization and is conducive to the stability of the algorithm performance such that the convergence performance of the algorithm is well maintained in the multi-objective optimization problem.

## 2) OVERALL PERFORMANCE ANALYSIS OF ALGORITHM

Table 4 shows the IGD index test results of MOEA/D-ANA and its comparative algorithms MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN with respect to generation. To more intuitively reflect the stability of the algorithm, Figure 10 shows the statistical box chart of the IGD index values of the four algorithms on the 3-5D DTLZ test function.

From the IGD index test results shown in Table 4, MOEA/D-ANA is strictly superior to MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN in terms of the DTLZ1 and DTLZ3 test problems, and MOEA/D-ANA is strictly superior to MOEA/D, MOEA/D-GR and MOEA/D-DN in terms of the DTLZ2 and DTLZ4. Except for the difference between 4- and 5-objective MOEA/D-ANA and MOEA/D-DU, the test results are strictly better or weaker

than MOEA/D-DU. This result shows that the quality of the solution set obtained by MOEA/DANA is obviously better than that of other comparison algorithms. The reason for this result is that the DTLZ2 and DTLZ4 problems are simple and continuous single-mode test problems, and the initial population is relatively close to the PF in the target space. When the population evolves to a certain algebra, MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN can obtain excellent solution sets. However, in the case of complex multimodal DTLZ1 and DTLZ3 test problems, MOEA/DANA can quickly converge to the PF and obtain a higher quality solution set. With the increase in objectives, the solution set quality of the algorithm is stable while the performance of the comparison algorithm is significantly reduced, which further reflects the performance of MOEA/D-ANA.

It can be observed from Figure 10 that compared with the four algorithms of MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN, the quaternion distance (the shortest box length) of MOEA/D-ANA is far less than that of the four comparison algorithms in the 3-5D DTLZ series test function, and the algorithm does not easily produce abnormal values or less abnormal values (the abnormal value is indicated by the red plus sign in the figure). Even if the algorithm produces such values, the outlier is not higher than the median of the other four algorithms. This result shows that the stability of the MOEA/D-ANA algorithm is strong and that the overall quality of the solution set is higher. In the

**TABLE 5. Running time of 5 algorithms on DTLZ problems (Unit: s.)**

Test Function	M	TIME <sub>mean</sub>				
		MOEA/D	MOEA/D-GR	MOEA/D-DU	MOEA/D-DN	MOEA/D-ANA
DTLZ1	3	32.64	98.17	114.07	29.53	<b>27.71</b>
	4	74.27	253.16	309.70	66.06	<b>60.51</b>
	5	119.09	422.51	488.76	97.52	<b>89.83</b>
DTLZ2	3	16.54	49.26	57.55	15.02	<b>14.26</b>
	4	18.82	63.46	79.00	16.91	<b>15.43</b>
	5	19.82	70.11	80.82	16.65	<b>15.43</b>
DTLZ3	3	33.30	99.08	113.95	30.18	<b>18.88</b>
	4	74.99	254.72	316.18	68.16	<b>62.16</b>
	5	119.67	422.83	488.30	101.26	<b>92.75</b>
DTLZ4	3	16.63	49.67	57.74	15.59	<b>14.57</b>
	4	18.87	63.01	73.04	16.99	<b>15.70</b>
	5	20.07	71.57	81.55	17.00	<b>15.73</b>

DTLZ1 and DTLZ3 test functions, the median (red line in the figure) of the MOEA/D-ANA algorithm is significantly lower than that of the four comparison algorithms. In the DTLZ2 and DTLZ4 test functions, the median values of MOEA/D-ANA and MOEA/D-DU are not significantly different and are significantly lower than those of MOEA/D, MOEA/D-GR and MOEA/D-DN, indicating that the algorithm has higher accuracy and better performance.

These phenomena more intuitively show that the MOEA/DANA algorithm can adaptively adjust the size of each generation neighborhood of each subproblem via the ANA strategy. This approach makes the limited algorithm resources more efficient, and it can enhance the stability of the algorithm performance and improve the overall quality of the solution set of the algorithm.

#### D. ALGORITHM CONVERGENCE ANALYSIS

The complexity of the algorithm is reflected in the number of computing resources needed to run the algorithm. The shorter the running time is, the less computing resources are needed, which shows that the lower the complexity of the algorithm and the better the performance of the algorithm. Table 5 shows the running time comparison data of MOEA/D-ANA, MOEA/D, MOEA/D-GR, MOEA/D-DU and MOEA/D-DN on DTLZ test functions.

From Table 5, it can be seen that for the same test problem, when the target dimensions are the same, the running time of MOEA/D-ANA algorithm is significantly lower than the other four comparison algorithms. It shows that the algorithm has low computational complexity and better performance. With the increase of the objective dimension, the calculation complexity of MOEA/D-GR and MOEA/D-DU increases rapidly, which shows that it is unreasonable to allocate the same neighborhood for each subproblem. MOEA/D-DN uses differentiated neighborhood, and its running time is significantly better than the first three comparison algorithms. However, this algorithm needs to test the appropriate neighborhood size for each test function in advance, and then set up neighborhood for each test function. The early test work of this algorithm is more complex and time-consuming. MOEA/D-ANA strategy uses adaptive method to allocate neighborhood for subproblems, and its robustness is less

affected by the increase of target dimension. It shows that the use of ANA strategy can effectively use algorithm resources, and make algorithm performance better.

#### V. CONCLUSION

To allocate limited algorithmic resources more efficiently, this paper proposes a decomposition multi-objective evolutionary algorithm (MOEA/D-ANA) based on the adaptive neighborhood adjustment strategy. This approach improves the convergence of the algorithm and the overall quality of the solution set and also balances the conflict between the convergence and diversity of the algorithm by adjusting the neighborhood scale of the same sub-problem in different evolution algebras with different values of parameter  $\beta$  and the neighborhood scale of different sub-problems in the same evolution algebras with the included angle  $\theta$  to reasonably allocate the limited algorithmic resources to different sub-problems in each generation. The experimental results indicate that the MOEA/D-ANA algorithm not only maximizes the utilization of limited algorithmic resources and significantly improves the performance of the algorithm but also shows good performance in addressing multi-objective optimization problems with complex Pareto solution sets. In future work, we will investigate extension of this idea to multi-objective optimization problems of complex Pareto solution sets and application to network optimization, path optimization, plant location and other problems in logistics.

#### REFERENCES

- [1] R. Wang, P. J. Fleming, and R. C. Purshouse, "General framework for localised multi-objective evolutionary algorithms," *Inf. Sci.*, vol. 258, pp. 29–53, Feb. 2014.
- [2] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the strength Pareto evolutionary algorithm," in *Proc. Evol. Methods Design, Optim. Control Appl. Ind. Prob. (EUROGEN)*, Athens, Greece, Sep. 2001, pp. 95–100.
- [3] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
- [4] K. Deb and J. Sundar, "Reference point based multi-objective optimization using evolutionary algorithms," in *Proc. 8th Annu. Conf. Genetic Evol. Comput. (GECCO)*, Washington, DC, USA., 2006, pp. 635–642.
- [5] N. Beume, B. Naujoks, and M. Emmerich, "SMS-EMOA: Multiobjective selection based on dominated hypervolume," *Eur. J. Oper. Res.*, vol. 181, no. 3, pp. 1653–1669, Sep. 2007.
- [6] J. Bader and E. Zitzler, "HypE: An algorithm for fast hypervolume-based many-objective optimization," *Evol. Comput.*, vol. 19, no. 1, pp. 45–76, Mar. 2011.
- [7] E. Zitzler and S. Künzli, "Indicator-based selection in multiobjective search," in *Proc. Int. Conf. Parallel Problem Solving From Nature*, vol. 3242. Berlin, Germany: Springer, 2004, pp. 832–842.
- [8] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Trans. Evol. Comput.*, vol. 11, no. 6, pp. 712–731, Dec. 2007.
- [9] R. Cheng, Y. Jin, M. Olhofer, and B. Sendhoff, "A reference vector guided evolutionary algorithm for many-objective optimization," *IEEE Trans. Evol. Comput.*, vol. 20, no. 5, pp. 773–791, Oct. 2016.
- [10] D. Gong, J. Sun, and X. Ji, "Evolutionary algorithms with preference polyhedron for interval multi-objective optimization problems," *Inf. Sci.*, vol. 233, pp. 141–161, Jun. 2013.
- [11] L.-P. Wang, M.-L. Feng, and Q.-Q. Qiu, "Survey on preference-based multi-objective evolutionary algorithms," *Chin. J. Comput.*, vol. 42, no. 6, pp. 1289–1315, Jul. 2019.

- [12] D. Gong, J. Sun, and Z. Miao, "A set-based genetic algorithm for interval many-objective optimization problems," *IEEE Trans. Evol. Comput.*, vol. 22, no. 1, pp. 47–60, Feb. 2018.
- [13] Y. Liu, D. Gong, J. Sun, and Y. Jin, "A many-objective evolutionary algorithm using a one-by-one selection strategy," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2689–2702, Sep. 2017.
- [14] W.-J. Kong, J.-L. Ding, and T.-Y. Chai, "Survey on large-dimensional multi-objective evolutionary algorithms," *Control Decis.*, vol. 25, no. 3, pp. 321–326, 2010.
- [15] Y. Qi, X. Ma, F. Liu, L. Jiao, J. Sun, and J. Wu, "MOEA/D with adaptive weight adjustment," *Evol. Comput.*, vol. 22, no. 2, pp. 231–264, Jun. 2014.
- [16] H. Li and Q. Zhang, "Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 13, no. 2, pp. 284–302, Apr. 2009.
- [17] K. Li, Q. Zhang, S. Kwong, M. Li, and R. Wang, "Stable matching-based selection in evolutionary multiobjective optimization," *IEEE Trans. Evol. Comput.*, vol. 18, no. 6, pp. 909–923, Dec. 2014.
- [18] Z. Wang, Q. Zhang, M. Gong, and A. Zhou, "A replacement strategy for balancing convergence and diversity in MOEA/D," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Beijing, China, Jul. 2014, pp. 2132–2139.
- [19] Y. Yuan, H. Xu, B. Wang, B. Zhang, and X. Yao, "Balancing convergence and diversity in decomposition-based many-objective optimizers," *IEEE Trans. Evol. Comput.*, vol. 20, no. 2, pp. 180–198, Apr. 2016.
- [20] Q. Zhang, W. Liu, and H. Li, "The performance of a new version of MOEA/D on CEC09 unconstrained MOP test instances," in *Proc. IEEE Congr. Evol. Comput.*, Trondheim, NO, USA, May 2009, pp. 203–208.
- [21] S.-Z. Zhao, P. N. Suganthan, and Q. Zhang, "Decomposition-based multi-objective evolutionary algorithm with an ensemble of neighborhood sizes," *IEEE Trans. Evol. Comput.*, vol. 16, no. 3, pp. 442–446, Jun. 2012.
- [22] H. Zhou and L.-P. Wang, "Decomposition multiobjective evolutionary algorithm of dynamic neighborhood," *J. Chin. Comput. Syst.*, vol. 38, no. 9, pp. 2039–2044, Sep. 2017.
- [23] L.-P. Wang, F. Wu, M.-Z. Zhang, and F.-Y. Qiu, "Decomposition multi-objective evolutionary algorithm based on differentiated neighborhood strategy," *Pattern Recognit. Artif. Intell.*, vol. 30, no. 12, pp. 1069–1082, Dec. 2017.
- [24] R. Wang, R. C. Purshouse, and P. J. Fleming, "Preference-inspired coevolutionary algorithms for many-objective optimization," *IEEE Trans. Evol. Comput.*, vol. 17, no. 4, pp. 474–494, Aug. 2013.
- [25] L. C. T. Bezerra, M. López-Ibáñez, and T. Stützle, "Comparing decomposition-based and automatically component-wise designed multi-objective evolutionary algorithms," in *Proc. Int. Conf. Evol. Multi-Criterion Optim.*, Cham, Switzerland, Mar. 2015, pp. 396–410.
- [26] Z. Wang, Q. Zhang, A. Zhou, M. Gong, and L. Jiao, "Adaptive replacement strategies for MOEA/D," *IEEE Trans. Cybern.*, vol. 46, no. 2, pp. 474–486, Feb. 2016.
- [27] D. A. Van Veldhuizen and G. B. Lamont, "On measuring multiobjective evolutionary algorithm performance," in *Proc Congr. Evol. Comput.*, Washington, DC, USA, Feb. 2002, pp. 204–211.
- [28] J. R. Schott, "Fault tolerant design using single and multicriteria genetic algorithm optimization," M.S. thesis, Massachusetts Inst. Technol., Boston, MA, USA, May 1995.
- [29] G.-Y. Yu, P. Li, Z. He, and Y.-M. Sun, "Advanced evolutionary algorithm used in multi-objective constrained optimization problem," *Comput. Integr. Manuf. Syst.*, vol. 15, no. 6, pp. 1172–1178, Jun. 2009.
- [30] E. Zitzler, K. Deb, and L. Thiele, "Comparison of multi-objective evolutionary algorithms: Empirical results," *Evol. Comput.*, vol. 8, no. 2, pp. 173–195, Feb. 2000.
- [31] K. Deb, L. Thiele, M. Laumanns, and E. Zitzler, "Scalable test problems for evolutionary multiobjective optimization," *Evol. Multi-objective Optim.*, Mar. 2006, pp. 105–145.



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