ISSN: 1813-4890

Research on multi-objective genetic algorithm based on improved neighbourhood search of non-dominated individuals

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Abstract

In order to prevent the premature problem of the multi-objective genetic algorithm, which is unable to find isolated points, and at the same time to avoid the generation of a large number of duplicate individuals, a multi-objective genetic algorithm based on the improvement of taboo search is proposed. It is proposed to construct the domain by incorporating the taboo search algorithm into the NSGA-Ⅱ, so that the non-dominated excellent individuals of its NSGA-Ⅱ are used as inputs to the taboo search, to strengthen the local search ability of the algorithm, while retaining its diversity as well as its distributivity. Secondly, to introduce the adaptive crossover variance probability formula to prevent the phenomenon of under-ripening convergence, and finally, to validate the convergence and distributivity of the algorithm through the classical ZDT test function, in combination with the evaluation indexes for convergence and distributivity of the algorithm.

Keywords

Multi-objective genetic algorithm, taboo search, algorithm optimisation.

1. Introduction

NSGA-Ⅱ adopts the non-dominated sorting mechanism to reduce the complexity of the algorithm, and the Pareto optimal solution set has good distribution. However, since NSGA-Ⅱ tends to produce duplicate individuals in the convergence process and fall into premature maturity, improvements for the NSGA-Ⅱ algorithm have been gradually proposed. Britto et al. [1] proposed a hybrid method based on NSGA-Ⅱ and Mamdani fuzzy inference system to solve the team allocation problem in agile software development projects. Zhang et al. [2] developed an NSGA-Ⅱ-TRA algorithm, which uses a new heuristic algorithm to constrain the constraint processing in NSGA-Ⅱ to solve the optimal test RAP. In [3], NSGA-Ⅱ is mixed with population initialization heuristic and heuristic crossover operator to solve a new two-objective production distribution supply chain scheduling model in a flow-hopping environment. Wen Gan et al. [4] use principles such as spatial three-way partitioning to construct heuristic algorithms and used NSGA-Ⅱ algorithm to generate the set of Pareto frontiers, and finally selected the optimal loading scheme with maximum volume utilization. Le Xiyou et al. [5] introduced the cooling thinking in simulated annealing algorithms in NSGA-Ⅱ, which provided a more reasonable criterion for the selection of populations and strengthened the diversity of the populations. In this paper, a non-dominated genetic sorting algorithm (NIDS-NSGA-Ⅱ) with improved taboo search is proposed, which introduces the idea of taboo search to achieve both local and global search capabilities to achieve better results while retaining the diversity and uniformity of its solution set.

ISSN: 1813-4890

2. Introduction to Algorithms

2.1. Introduction to Taboo Search

Taboo search is a single-solution metaheuristic algorithm proposed by Glover [6][7], which is widely used to solve various combinatorial optimization problems [8]. The core idea is to break out of the local optimal solution and iterate towards the global optimal solution through local search and memory mechanisms. Taboo search utilizes taboo lists to store previous decisions to avoid repeated execution of recent moves, thus effectively preventing falling into a loop. For example, in the traveling salesman problem, taboo search effectively guides the traveler to find the optimal path, even in the vicinity of the local optimum. It accomplishes this by recording historical moves and using a taboo list to limit the repetition of moves, ultimately enabling the discovery of a more optimal solution.

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2.2. Multi-objective genetic algorithm

2.2.1. Introduction to NSGA

Non-dominated Sorting Genetic Algorithms [9] (NSGA for short), proposed by Deb and Srinivas, introduced ideas based on the concept of Pareto optimality in multi-objective optimization problems with remarkable success. The main differences between NSGA and simple genetic algorithms are the introduction of the concepts of non-dominated sorting and stratification, while its basic selection, crossover, and mutation operations remain unchanged. The algorithm facilitates stratification by non-dominated sorting of individuals prior to selection operations and by introducing virtual fitness values and microhabitats to ensure the survival chances of superior individuals and to conserve the diversity of the population. By introducing the concepts of non-dominated sorting and stratification, NSGA is able to solve this type of problem efficiently and produce a set of Pareto-optimal solutions with equilibrium and diversity. The specific flow of the NSGA algorithm is shown in Fig.1.

2.2.2. Introduction to NSGA-Ⅱ

Deb [10] proposed an improved Non-dominated Sorting Genetic Algorithm with Elite Strategies (NSGA-Ⅱ), which optimizes the underlying NSGA algorithm. In order to reduce the complexity of the algorithm and improve performance, a fast non-dominated sorting method was proposed. The method introduces crowding and crowding comparison algorithms aimed at ensuring uniform distribution and diversity of the population. By considering the crowding degree of individuals in the selection operation, the diversity of the population can be effectively maintained, and the aggregation of local optima can be avoided. In addition, an elite strategy is used to pass on the best individuals to the next generation, further improving the algorithm's performance. Through these adjustments, while ensuring the efficiency of the algorithm, it becomes more likely that excellent individuals will be retained and developed in the population, thereby improving the convergence speed and search quality of the algorithm.

(1) Fast non-dominated sorting

Assuming that the current algorithmic population is P, the two parameters that determine each individual p in the population are i_p (the number of dominating individuals p in the population) and j_p (the number of individuals in the population dominated by individual p). The main procedure is to first find the number of i_p=0 individual p in the population, and save it in the set F1; continue to find the individual i in the current set F1, and the set of dominated individuals is Mi, and iterate through the individual l, and execute i_l= i_l -0. If i_l=0, then save individual l in a new set H, call the individual obtained in F1 as the first non-dominated individual, and repeat the above operation starting from the new set H until the whole population is graded.

(2) Congestion distance and congestion distance operator

The concept of crowding is the density of individuals around a given individual. Crowding distance is primarily concerned with maintaining the diversity of individuals in a population. Specifically, it is generally defined as the density of individuals in a single sorting stratum after the population has been sorted non-dominantly according to the dominance relation. It is commonly used in multi-objective algorithms for dominance relations such as in NSGA-Ⅱ. As shown in Fig.2, the crowding distance of individual i can be visually represented by the rectangle in the figure.

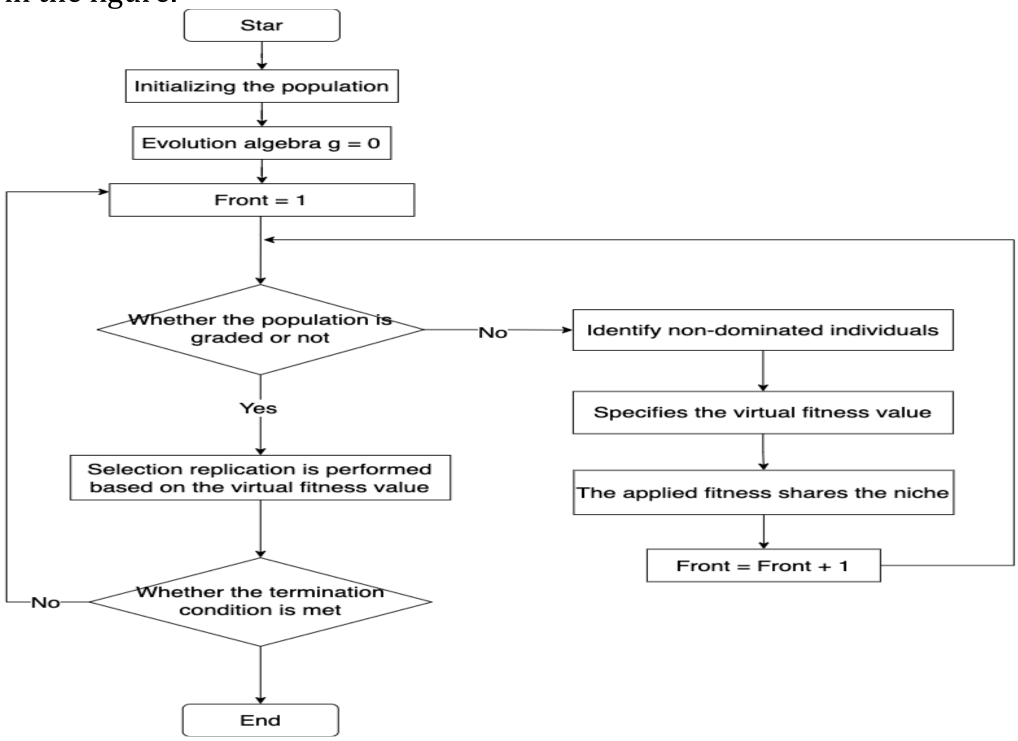

Fig. 1 Basic flow chart of NSGA

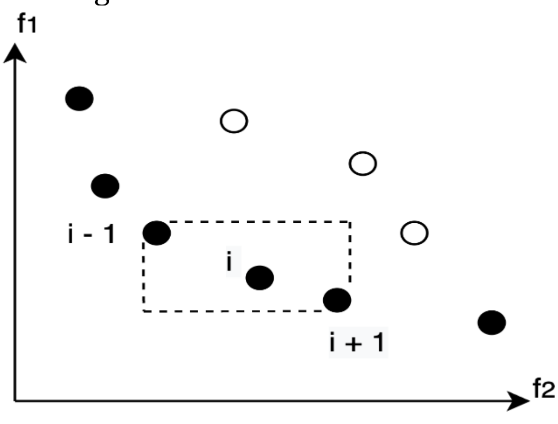

Fig. 2 Congestion image

3. TS-NSGA-Ⅱ Algorithm

3.1. Combination of taboo search and improved fast non-dominated sorting genetic algorithm with elite strategy

The advantages of NSGA-Ⅱ are that it runs efficiently and the resulting solution set is well-distributed, and its main shortcomings are that it is difficult to find isolated points and it is easy to produce a large number of duplicate individuals. In order to overcome the above shortcomings, this paper proposes an improved NSGA-Ⅱ algorithm, which is mainly improved in the following two aspects.

3.1.1. Non-dominated Individual Domain Search Strategie

In this paper, we introduce the taboo search algorithm [11] with the aim of increasing the diversity as well as homogeneity of the solution set. Let the solution set after merging be R = P ∪ GA ∪ TS, where P is the parent individual, GA is the individual obtained by the genetic operator, and TS is the individual obtained by the taboo search operator. Secondly, the first N individuals are selected from R by the non-dominated ordering and congestion distance as the next generation of parent individuals R+1. Through this operation, the advantages of NSGA-Ⅱ in avoiding the loss of good individuals in the parent generation can be retained, while the local search capability is enhanced, which in turn reduces the number of duplicates in the offspring and enhances the diversity of the solution set.

The strategy for taboo search is as follows:

(1) Initial solution

The taboo search algorithm has a high dependence on the initial solution, so the initial solution is randomly selected from the individuals whose parents have a non-dominated ordering of 1 and whose crowding is not infinite.

(2) Neighbourhood solutions

The initial iteration, in order to increase the probability of finding the optimal solution, expands the search range. As the iteration proceeds step by step, the resulting solution tends to be close to the optimal solution. Therefore, the search range should be reduced to avoid repeated searches. The neighborhood generation as well as the search range are updated according to the following equations, respectively:

$$X_i = X_0 + rand \times scale \times (U_X - L_X) \tag{1}$$

$$scale = 1 - sigmoid \tag{2}$$

(3) Candidate solutions

For a given individual X, it is computationally intensive to compute all its neighborhood solutions, so a certain strategy is needed to select the candidate solutions. In this paper, we use non-dominated ordering and congestion operator to select a certain number of solutions as candidate solutions N(x) from inside the given candidate solutions.

(4) Flouting the Guidelines

$X \in opt\{N(x)\}$, if there exists $X \prec Xbest$, then X is chosen as the next current solution.

(5) Table of contraindications

The current solution X has been forbidden if and only if $\forall X_j \in TabuList$, which satisfies that the individual's current congestion distance extreme difference is greater than the previous generation's congestion distance extreme difference.

3.1.2. Adaptive crossover operators and variational operators

In genetic algorithms, the crossover operator acts as the primary operator for global search, and the mutation operator acts as the secondary operator for local search. Genetic algorithms work with each other through the pair of operators, crossover and mutation, to obtain a stronger search capability while maintaining population diversity to prevent premature convergence. In the NSGA-Ⅱ algorithm, because the target involves more than one fitness value, adaptive crossover mutation probability does not apply to a specific fitness value to participate in the calculation. Therefore, the formula is changed to adjust adaptively only according to the number of generations, no longer relying on fitness value. The specific method is shown in Eq:

$$P_c=0.15\times\sin(g/G\times\pi+\pi/2)+0.65 \tag{3}$$

$$P_m=0.04\times\sin(g/G\times\pi-\pi)/2+0.65 \tag{4}$$

where gen is the current evolutionary generation of the population; G is the total number of iterations of the algorithm.

3.2. NIDS-NSGA-Ⅱ algorithm flow

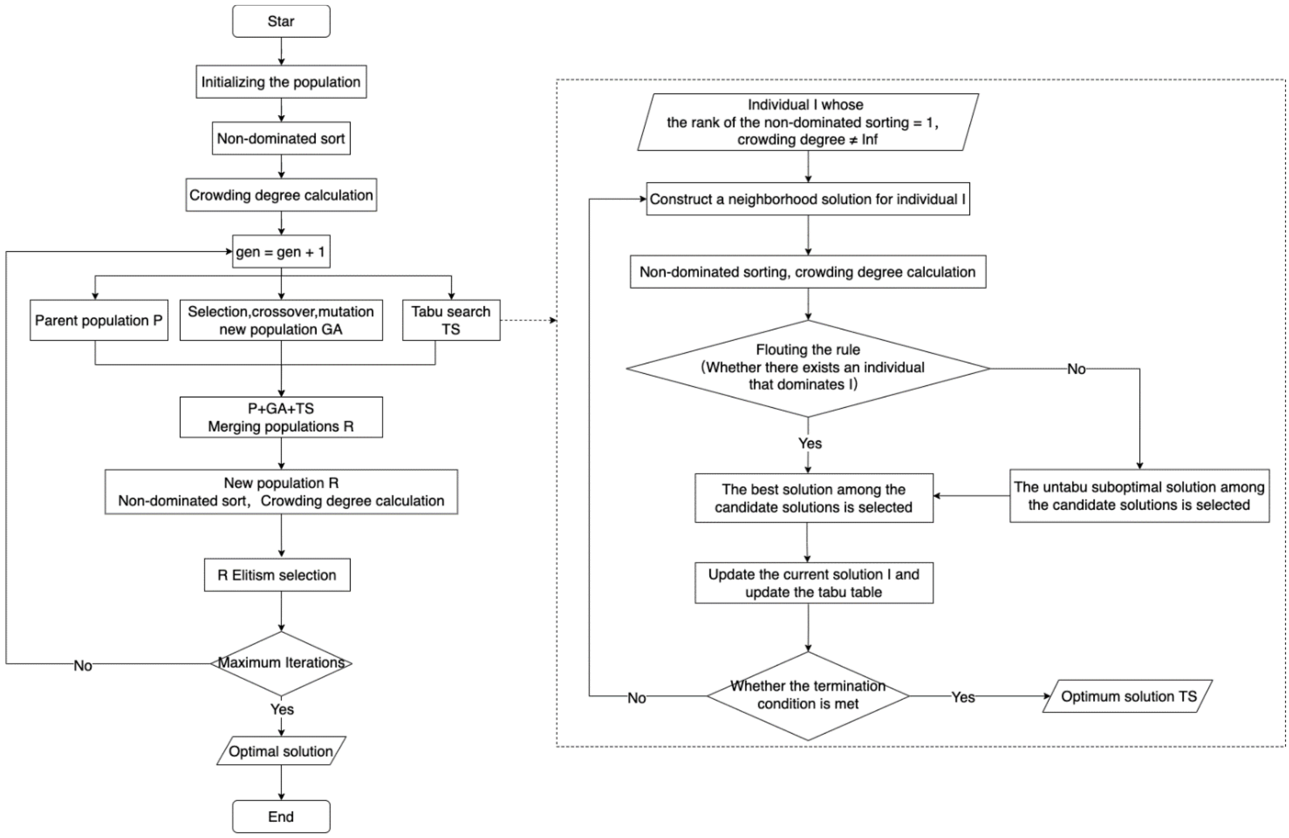

Fig. 3 Algorithm flowchart

4. Experimental design and results

4.1. NIDS-NSGA-Ⅱ algorithm flow

The main test functions used in this paper are ZDT1, ZDT2, and ZDT3 of the ZDT series test functions. The algorithm performance evaluation adopts the comprehensive index IGD, the convergence index GD, and the diversity index SP as the evaluation criteria.

Inverse Generation Distance (IGD) evaluates the convergence and diversity of the algorithm by measuring the proximity between the real Pareto frontiers and those obtained by the algorithm. Generation Distance (GD) evaluates the convergence of the algorithm by measuring the distance between the Pareto frontiers obtained by the algorithm and the real Pareto frontiers. Spacing (SP) measures whether the individuals in the Pareto frontiers obtained by the algorithm are evenly distributed. SP is used to assess whether the individuals in the Pareto front obtained by the algorithm are evenly distributed.

ISSN: 1813-4890

4.2. Experimental results

The improved algorithm was tested with a standard test function, and the improved NIDS-NSGA-Ⅱ algorithm was compared with the original NSGA-Ⅱ algorithm. The relevant parameters of the NSGA-Ⅱ algorithm were set as follows: the crossover probability was specified to be 0.6, and the variance probability was specified to be 0.03; the population size was set to be 200, and the number of evolutionary generations was set to be 200.

4.3. Experimental analyses

In order to measure the performance of the improved algorithms more comprehensively, this section introduces the evaluation indices of inverse generation distance (IGD), generation distance (GD), and spacing (SP), which are commonly used in multi-objective optimization problems. The improved algorithms are referred to as NIDS-NSGA-Ⅱ here. For the three algorithms to be tested, each experiment is run independently 20 times, and the values of inverse generation distance (IGD), generation distance (GD), and spacing (SP) of each algorithm when testing the ZDT function are recorded. The optimal value, the worst value, the extreme value of the range difference, the mean, the standard deviation, and the variance are retained, and the specific numerical results are shown in Tables 1-1, 1-2, and 1-3.

Table 1-1 Comparative Values of IGD Indicators

test function	arithmetic	optimum value	minimum value	Range Extreme	average value	standard deviation	variance
ZDT1	NSGA-Ⅱ	0.0032	0.0050	0.0017	0.0039	5.30E-04	2.81E-07
	NIDS-NSGA-Ⅱ	0.0027	0.0046	0.0019	0.0034	4.25E-04	1.81E-07
ZDT2	NSGA-Ⅱ	0.0028	0.0057	0.0029	0.0038	7.48E-04	5.59E-07
	NIDS-NSGA-Ⅱ	0.0027	0.0040	0.0013	0.0034	3.15E-04	9.91E-08
ZDT3	NSGA-Ⅱ	0.0031	0.0054	0.0024	0.0042	6.85E-04	4.69E-07
	NIDS-NSGA-Ⅱ	0.0029	0.0049	0.0049	0.0036	4.84E-04	2.34E-07

In Table 1-1, the optimal values of IGD metrics on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm after 20 independent experiments for ZDT1 function are 0.0032 and 0.0027, respectively. The optimal values of IGD metrics on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm after 20 independent experiments for ZDT2 function are 0.0028 and 0.0027, respectively. For the ZDT3 function after 20 independent experiments, the optimal values of IGD metrics on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 0.0031 and 0.0029, respectively. In terms of variance metrics, the values of ZDT1 function on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 2.81E-07 and 1.81E-07, respectively. The values of ZDT2 function on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 5.59E-07 and 9.91E-08, respectively. The values of ZDT3 function on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 4.69E-07 and 2.34E-07, respectively. Overall, the values of IGD metrics obtained by the NIDS-NSGA-Ⅱ algorithm are better in overall test function metrics.

Table 1-2 Comparative values of GD indicators

test function	arithmetic	optimum value	minimum value	Range Extreme	average value	standard deviation	variance
ZDT1	NSGA-Ⅱ	0.0080	0.0124	0.0043	0.0097	1.33E-03	1.76E-06
	NIDS-NSGA-Ⅱ	0.0069	0.0115	0.0046	0.0084	1.06E-03	1.13E-06
ZDT2	NSGA-Ⅱ	0.0071	0.0143	0.0072	0.0096	1.87E-03	3.49E-06
	NIDS-NSGA-Ⅱ	0.0068	0.0101	0.0032	0.0086	7.87E-04	6.19E-07
ZDT3	NSGA-Ⅱ	0.0021	0.0037	0.0016	0.0028	4.66E-04	2.17E-07
	NIDS-NSGA-Ⅱ	0.0020	0.0033	0.0013	0.0024	3.29E-04	1.08E-07

In Table 1-2, the optimal values of the ZDT1 function for the GD metrics on the NSGA-Ⅱ algorithm and the NIDS-NSGA-Ⅱ algorithm after 20 independent experiments are 0.0080 and 0.0069, respectively. The optimal values of the ZDT2 function for the GD metrics on the NSGA-Ⅱ algorithm and the NIDS-NSGA-Ⅱ algorithm after 20 independent experiments are 0.0071 and 0.0068, respectively. For the ZDT3 function after 20 independent experiments, the optimal values of GD indicator on NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 0.0021 and 0.0020 respectively. Meanwhile, the five evaluation factors of GD indicator, namely, worst value, extreme value of the range difference, mean, standard deviation, and variance are analyzed, and the improved NIDS-NSGA-Ⅱ algorithm is more superior.

Table 1-3 Comparative values of SP indicators

test function	arithmetic	optimum value	minimum value	Range Extreme	average value	standard deviation	variance
ZDT1	NSGA-Ⅱ	0.0026	0.0034	0.0008	0.0030	2.14E-04	4.59E-08
	NIDS-NSGA-Ⅱ	0.0028	0.0036	0.0007	0.0033	1.96E-04	3.84E-08
ZDT2	NSGA-Ⅱ	0.0028	0.0035	0.0008	0.0031	1.95E-04	3.82E-08
	NIDS-NSGA-Ⅱ	0.0028	0.0037	0.0008	0.0033	2.49E-04	6.20E-08
ZDT3	NSGA-Ⅱ	0.0038	0.0046	0.0008	0.0042	2.38E-04	5.65E-08
	NIDS-NSGA-Ⅱ	0.0040	0.0046	0.0006	0.0043	1.85E-04	3.41E-08

In Table 1-3, for the ZDT1 function after 20 independent experiments, the optimal values of SP metrics on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 0.0026 and 0.0028, respectively. For the ZDT2 function after 20 independent experiments, the optimal values of SP metrics on the NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 0.0028 and 0.0028, respectively. For the ZDT3 function after 20 independent experiments, the optimal values of SP metrics on NSGA-Ⅱ algorithm and NIDS-NSGA-Ⅱ algorithm are 0.0038 and 0.0040, respectively. In terms of SP standard deviation and variance metrics, both ZDT1 function and ZDT2 function have outstanding performance. In general, the NIDS-NSGA-Ⅱ algorithm is more stable than the NSGA-Ⅱ algorithm in terms of SP metrics.

In summary, it can be concluded that the improved multi-objective genetic algorithm performs better than the traditional NSGA-Ⅱ algorithm in terms of convergence and performance results.

5. Conclusion

The comparison results of IGD, GD, and SP show that the NIDS-NSGA-Ⅱ algorithm, incorporating the idea of taboo search, is better than the NSGA-Ⅱ algorithm in solving large-scale variable optimization problems in terms of solution accuracy and operational efficiency. The introduction of the taboo search algorithm avoids the solution process from falling into local optimality on the one hand and retains the outstanding individuals of the parent population on the other hand, which increases the diversity of the population. The advantage is more obvious with the increase of independent variables. Therefore, NIDS-NSGA-Ⅱ has better uniformity and convergence in solving multi-objective functions with large-scale variables.

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