Dynamic Constrained Multi-objective Evolutionary Algorithms with A Novel Selection Strategy for Constrained Optimization

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ABSTRACT

The recently proposed dynamic constrained multi-objective evolutionary algorithm (DCMOEA) is effective to handle constrained optimization problems (COPs). However, one drawback of DCMOEA is it mainly searches the global optimum from infeasible regions, which may result in the bias against feasible solutions. Then the useful information about the optimal direction of feasible regions is not fully used. To overcome this defect, this paper proposes a novel selection strategy based on DCMOEA framework, called NSDCMOEA to solve COPs. The performance of NSDCMOEA is evaluated using a set of benchmark suites. Experimental results validate that the proposed method is better than or very competitive to five state-of-the-art algorithms.

KEYWORDS

Constraint-handling, Multi-objective, Constrained optimization

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1 INTRODUCTION

One key issue for constraint-handling evolutionary algorithms (EAs) is how to effectively balance the search of solutions between feasible and infeasible regions. The basis of this problem solving is how to handle the relationship between feasible and infeasible solutions. Ideally, solutions in a population should come from two directions of the global optimum, both feasible and infeasible directions. Nevertheless, most constraint-handling mechanisms approach the global optimum either from infeasible or feasible direction.

Dynamic multiobjective evolutionary algorithms have been successfully used for solving unconstrained and COPs [3, 7, 8]. However, one drawback of DCMOEA [7] is that it searches the global optimum mainly from infeasible regions due to the multi-objective selection strategy. Considering the feasibility of the global optimum, solutions in feasible regions are also conducive to searching for the global optimum, so that there is a bias against feasible solutions for DCMOEA during the selection process. To address this issue, this paper proposes a novel selection strategy based on DCMOEA framework named NSDCMOEA to deal with COPs. The proposed NSDCMOEA aims at alleviating the greediness for infeasible solutions of the DCMOEA by giving priority to selection of feasible solutions. Experimental results indicate that the proposed method is effective and generally performs better than five state-of-the-art algorithms.

2 DCMOEA

In DCMOEA [7], a COP was converted into an equivalent dynamic constrained three-objective optimization problem: the original objective, a constraint-violation objective and a niche-count objective. The constraint violation objective is used to handle the constraint difficulty, while the niche-count objective is applied to address the multimodal difficulty.

3 THE PROPOSED NSDCMOEA

The main difference between the proposed NSDCMOEA and DCMOEA lies in the design of the selection strategy. Since constraints split the search space into feasible and infeasible

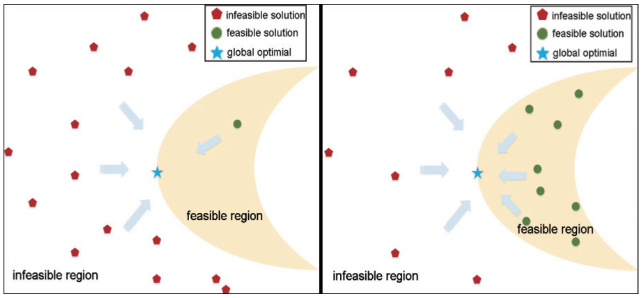

Figure 1: Evolution progress for DCMOEA (left) and NSDCMOEA (right).

regions, the way to design a reasonable selection strategy, which takes full advantage of information in such two regions, naturally becomes a key issue. The major purpose of NSDCMOEA is to ensure that the number of solutions in feasible regions and infeasible regions account for about a half of the population size, respectively. To realize it, once feasible solutions are found, solutions within promising feasible regions will take precedence over others during the selection process. If the size of feasible solutions are less than a half of the population size, we directly add all these feasible ones to the next population. Otherwise, we first select a half of the population size feasible solutions based on non-dominated sorting[1]. Then additional solutions will be chosen based on non-nominated sorting as well. In this way, if feasible solutions are provided in the population, they will take preference over infeasible ones during selection procedure.

Figure 1 illustrates the distribution of solutions both for feasible and infeasible regions. As shown in Figure 1, DCMOEA searches the global optimum from infeasible regions where most of solutions are located. In contrast, for NSDCMOEA, many promising feasible solutions are reserved, thus the direction of optimal searching is both form feasible and infeasible regions.

4 EXPERIMENTAL RESULTS

In this section, we evaluate the proposed method on a well-known benchmark test set CEC 2010 [4](D=10 and D=30). Moreover, the performance of NSDCMOEA is compared with five state-of-the-art methods: DCMOEA[7], εADE [5], CMODE [6], AIS [9], and ECHT-ARMOR-DE [2]. The Wilcoxon's test and Friedman's test results for these six algorithms are summarized in Tables 1 and 2. From Table 1, it can be observed that NSDCMOEA outperforms five algorithms since it provides higher R+ values than R- values in all the cases. Moreover, from Table 2, we can see that NSDCMOEA achieves the best ranking among six algorithms both for D=10 and D=30.

5 CONCLUSIONS

In this paper, a novel selection strategy based on DCMOEA framework, called NSDCMOEA is proposed. In NSDCMOEA, the search of global optimum can both from feasible and infeasible regions. Experimental results show the overall performance of NSDCMOEA is better than or very competitive to five state-of-the-art constraint-handling EAs.

Table 1: Results of Wilcoxon's test.

NSDCMOEA vs	D=10		D=30	
	R^+	R^-	R^+	R^-
CMODE	96.0	9.0	123.0	30.0
εADE	114.0	6.0	126.0	27.0
AIS	94.0	59.0	93.0	78.0
ECHT-ARMOR-DE	39.0	27.0	79.0	57.0
DCMOEA	32.0	4.0	63.0	15.0

R+, R- represent sum of ranks. That R+ > R- means that the algorithm of this paper is better than the compared algorithm and vice versa.

Table 2: Average ranks by Friedman's test.

Algorithm	Average ranks	
	D=10	D=30
NSDCMOEA	**2.75(1)**	**2.72(1)**
AIS	3.19(3)	3.17(3)
ECHT-ARMOR-DE	2.89(2)	3.39(4)
DCMOEA	3.25(4)	3.03(2)
CMODE	4.53(6)	3.97(5)
εADE	4.39(5)	4.72(6)

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