Effects of Removing Overlapping Solutions on the Performance of the NSGA-II Algorithm

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Abstract. The focus of this paper is the handling of overlapping solutions in evolutionary multiobjective optimization (EMO) algorithms. In the application of EMO algorithms to some multiobjective combinatorial optimization problems, there exit a large number of overlapping solutions in each generation. We examine the effect of removing overlapping solutions on the performance of EMO algorithms. In this paper, overlapping solutions are removed from the current population except for a single solution. We implement two removal strategies of overlapping solutions. One is the removal of overlapping solutions in the objective space. In this strategy, one solution is randomly chosen among the overlapping solutions with the same objective vector and left in the current population. The other overlapping solutions with the same objective vector are removed from the current population. As a result, each solution in the current population has a different location in the objective space. It should be noted that the overlapping solutions in the objective space are not necessary the same solution in the decision space. Thus we also examine the other strategy where the overlapping solutions in the decision space are removed from the current population except for a single solution. As a result, each solution in the current population has a different location in the decision space. The effect of removing overlapping solutions is examined through computational experiments where each removal strategy is combined into the NSGA-II algorithm.

1 Introduction

The design of evolutionary multiobjective optimization (EMO) algorithms has been discussed in the literature to find well-distributed Pareto-optimal or near Pareto-optimal solutions as many as possible (e.g., see Coello et al. [1] and Deb [2]). The handling of overlapping solutions, however, has not been discussed explicitly in many studies. This is mainly because the performance evaluation of EMO algorithms has been performed through computational experiments on multiobjective optimization problems with a large number of Pareto-optimal solutions. Since EMO algorithms usually have diversity-preserving mechanisms, many overlapping solutions are not likely to exist in each generation when they are applied to multiobjective optimization problems with continuous decision variables and/or many objective functions. On the other hand, the handling of overlapping solutions becomes an important issue in the application of EMO algorithms to multiobjective combinatorial optimization

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problems with only a few objective functions. In such an application, there may exist a large number of overlapping solutions in each generation as we will show in this paper through computational experiments on some test problems.

In this paper, we examine the effect of removing overlapping solutions on the performance of EMO algorithms. Overlapping solutions are removed from the current population. We examine two removal strategies of overlapping solutions. One removal strategy is performed in the objective space. Only a single solution among the overlapping solutions with the same objective vector is left in the current population. That is, overlapping solutions are removed so that each solution in the current population has a different location in the objective space. It should be noted that the overlapping solutions with the same objective vector are not necessary the same solution in the decision space. Thus we also examine the other strategy where the removal of overlapping solutions is performed in the decision space. Only a single solution among the overlapping solutions with the same decision vector is left in the current population. That is, overlapping solutions are removed so that each solution in the current population has a different location in the decision space. In this strategy, multiple solutions with the same objective vector can exist in the current population if they are not the same solution in the decision space.

The effect of removing overlapping solutions on the performance of EMO algorithms is examined through computational experiments on multiobjective 0/1 knapsack problems where each removal strategy is combined into the NSGA-II algorithm of Deb et al. [3]. First we show that there actually exist a large number of overlapping solutions in each generation in the application of the NSGA-II algorithm to two-objective 0/1 knapsack problems. Next we show that the removal of overlapping solutions improves the performance of the NSGA-II algorithm on those test problems especially in terms of the diversity of obtained non-dominated solutions. No clear differences are observed in the performance between the two removal strategies. Finally we show that these two removal strategies have a large effect on the performance of the NSGA-II algorithm when they are used together with a weighted sum-based tournament selection scheme of parent solutions with a large tournament size. This may be because a good balance is realized between the diversity-preserving effect of the removal strategies and the high selection pressure toward the Pareto front by the weighted sum-based parent selection scheme.

2 Handling of Overlapping Solutions

The original NSGA-II algorithm of Deb et al. [3] has no explicit mechanism to remove overlapping solutions while smaller fitness values are likely to be assigned to overlapping solutions than non-overlapping ones with the same non-dominated rank due to its diversity-preserving mechanism. In this section, we first briefly explain the NSGA-II algorithm. Then we explain two strategies for removing overlapping solutions, each of which is combined into the NSGA-II algorithm in computational experiments on multiobjective 0/1 knapsack problems in the next section.