Optimization of Scalarizing Functions Through Evolutionary Multiobjective Optimization

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Abstract. This paper proposes an idea of using evolutionary multiobjective optimization (EMO) to optimize scalarizing functions. We assume that a scalarizing function to be optimized has already been generated from an original multiobjective problem. Our task is to optimize the given scalarizing function. In order to efficiently search for its optimal solution without getting stuck in local optima, we generate a new multiobjective problem to which an EMO algorithm is applied. The point is to specify multiple objectives, which are similar to but different from the scalarizing function, so that the location of the optimal solution is near the center of the Pareto front of the generated multiobjective problem. The use of EMO algorithms helps escape from local optima. It also helps find a number of alternative solutions around the optimal solution. Difficulties of Pareto ranking-based EMO algorithms in the handling of many objectives are avoided by the use of similar objectives. In this paper, we first demonstrate that the performance of EMO algorithms as single-objective optimizers of scalarizing functions highly depends on the choice of multiple objectives. Based on this observation, we propose a specification method of multiple objectives for the optimization of a weighted sum fitness function. Experimental results show that our approach works very well in the search for not only a single optimal solution but also a number of good alternative solutions around the optimal solution. Next we evaluate the performance of our approach in comparison with a hybrid EMO algorithm where a single-objective fitness evaluation scheme is probabilistically used in an EMO algorithm. Then we show that our approach can be also used to optimize other scalarizing functions (e.g., those based on constraint conditions and reference solutions). Finally we show that our approach is applicable not only to scalarizing functions but also other single-objective optimization problems.

1 Introduction

Evolutionary multiobjective optimization (EMO) is one of the most active research areas in the field of evolutionary computation. EMO algorithms have been successfully applied to various application areas involving multiple objectives [2]. In some cases, EMO algorithms can outperform single-objective evolutionary algorithms even when they are used to solve single-objective problems. It was reported in some studies on multiobjectivization [15], [18] that better results were obtained by

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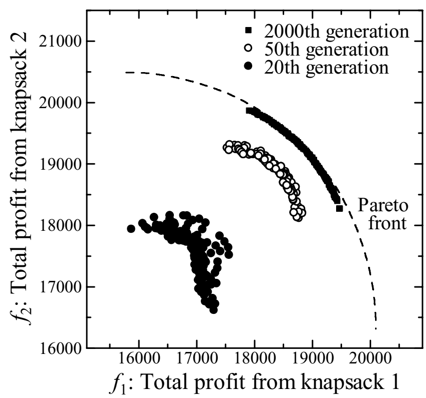
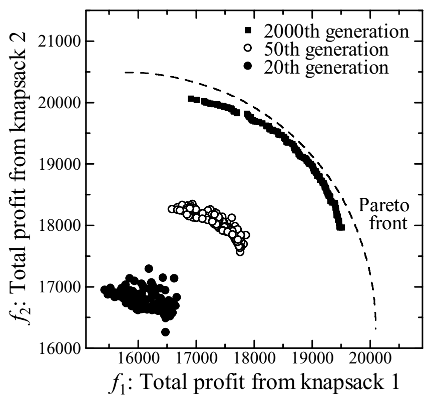
transforming single-objective problems into multiobjective ones (see [15] for multiobjectivization).

Motivated by these studies on multiobjectivization, we examined the use of EMO algorithms to optimize the sum of multiple objectives in our former studies [8], [10]. We obtained promising results when we used NSGA-II [3] to optimize the simple sum fitness function for a two-objective 500-item (i.e., 2-500) knapsack problem of Zitzler & Thiele [19]. That is, NSGA-II outperformed its single-objective version in finding the optimal solution of the sum of the two objectives. This is because the use of NSGA-II helps escape from local optima.

Usually EMO algorithms are very good at finding Pareto-optimal or near Pareto-optimal solutions around the center of the Pareto front of a two-objective problem. EMO algorithms, however, are not always good at finding good solutions near the edge of the Pareto front. This is illustrated in Fig. 1 where NSGA-II was applied to the 2-500 knapsack problem [19] using two different settings. In Fig. 1 (a), standard parameter values were used (i.e., 0.8 crossover probability and 1/500 mutation probability). In this case, we observe a good convergence of solutions to the Pareto front. Actually NSGA-II outperformed its single-objective version in finding the optimal solution of the simple sum fitness function: $fitness(\mathbf{x}) = f_1(\mathbf{x}) + f_2(\mathbf{x})$. On the other hand, lower crossover and higher mutation probabilities were used in Fig. 1 (b) in order to increase the diversity of solutions. The increase in the diversity of solutions in Fig. 1 (b) was achieved at the cost of the deterioration in the convergence to the Pareto front. Experimental results in Fig. 1 suggest that the direct use of EMO algorithms is not a good choice for finding the optimal solution of a weighted sum fitness function with very different weight values such as $fitness(\mathbf{x}) = 0.1 f_1(\mathbf{x}) + 0.9 f_2(\mathbf{x})$.



(a) Crossover 0.8 and mutation 1/500



(b) Crossover 0.2 and mutation 5/500

Fig. 1. Experimental results of NSGA-II on the 2-500 knapsack problem using two different settings of the crossover and mutation probabilities

Another weakness of EMO algorithms is the difficulty in the handling of many objectives. Most EMO algorithms are based on Pareto ranking to evaluate the fitness of each solution. Pareto ranking-based EMO algorithms, however, do not work well on