Genetic and Evolutionary Computation COnference 2002 GECCO

New York

July 9-13, 2002

Comparison of Multiobjective Optimization Evolutionary Algorithms for a Three-objective Problem

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Abstract

This paper presents a systematic comparative study of CMEA (constraint method-based evolutionary algorithm) with several other commonly reported mulitobjective evolutionary algorithms (MOEAs) in solving a three-objective optimization problem. The best estimate of the noninferior space was also obtained by solving this MO problem using a binary linear programming procedure. Several quantitative metrics are used in this study to compare the noninferior solutions with respect to relative accuracy, as well as spread and distribution of solutions in the noninferior space. Results based on multiple random trials of the MOEAs indicate that overall CMEA performs better than the other MOEAs for this three-objective problem.

1 Introduction

With the recent emergence of interest in solving realistic multiobjective (MO) problems, numerous multiobjective evolutionary algorithms (MOEAs) have been reported in the literature. While most of them have been successfully tested and evaluated for an array of two-objective test problems, little work is reported on solving MO problems with more than two objectives. Building upon the study reported by Zitzler et al. (2001) for a three-objective problem, this paper reports a comparison of performance of the constraint method-based evolutionary algorithm (CMEA) (Ranjithan et al. 2001, Kumar 2002) with those of SPEA-II (Zitzler et al. 2001), NSGA-II (Deb et al. 2000), and PESA (Corne et al. 2000). These results are also compared with the noninferior set obtained using a MO analysis with a binary linear programming procedure. An array of quantitative metrics is used to conduct a systematic performance comparison among the solutions generated by these MOEAs. In addition to several existing metrics that are extended from the original definitions for two objectives, a new one is defined to evaluate the relative degree of dominance of one set of noninferior solutions over another. As computational needs associated with each MOEA scale up differently with the increase in the number of objectives, the total number of evaluations required to generate the noninferior sets used in this comparative study are kept to be similar. Thus the comparisons represent the quality of the noninferior solutions obtained with similar computational effort.

The next section provides a brief background on CMEA. The subsequent section describes the performance metrics used in this study. Section 4 defines the test problem and a comparison of the results, followed by conclusions.

5 Conclusions

Comparing the noninferior solutions obtained using the MOEAs with those obtained using BLP (which is the best estimate available), CMEA performs relatively well in finding noninferior solutions that are close to the best available estimation, as well as in covering most of the noninferior surface for the thee-objective extended knapsack problem. When comparing the solutions obtained by the different MOEAs tested in this study, CMEA performs better than all others with respect to the spread of solutions in the noninferior space. While CMEA is able to generate a good distribution of solutions in a wider range of the noninferior space, the other MOEAs generate a high density of solutions in the central portion of the noninferior space. In the context of accuracy or degree of dominance, the CMEA solutions dominate those generated by the other MOEAs relatively more frequently. As the total number of function evaluations were kept similar for the different MOEAs, all the comparisons reflect the quality of the resulting noninferior solutions obtained using each MOEA.

While this study provides a systematic comparison of several MOEAs for a three-objective MO problem, further testing and evaluation studies are needed. Similar to the large array of test problems used in two-objective MO optimization, additional three-objective test problems reflecting different problem complexities need to be defined and be used in further comparative studies of these MOEAs. Also, the implications of MO problem scale up on the computational needs of the different MOEAs need to be investigated.