Efficient and Reliable Evolutionary Multiobjective Optimization Using ε-Dominance Archiving and Adaptive Population Sizing

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1 Introduction

This paper introduces a new algorithm, termed as the **ε**-NSGA-II that enables the user to specify the precision with which they want to quantify the Pareto optimal set and all other parameters are automatically specified within the algorithm. The development of the ε-NSGA-II was motivated by the steady state **ε**-MOEA developed by Deb et al [3]. The next section briefly describes the ε-NSGA-II.

2 Overview of the ε-NSGA-II Approach

The ε-NSGA-II is implemented using three primary steps. In the first step, the problem is solved using the original NSGA-II and parameters for crossover and mutation suggested by Deb [1]. The initial population size is set arbitrarily small (i.e., 5 in this paper) to ensure the algorithm's initial search is done using a minimum number of function evaluations. Subsequent increases in the population size adjust to the population size commensurate with problem difficulty. In the second step, the ε-NSGA-II uses a fixed sized archive to store the nondominated solutions generated in every generation of the NSGA-II runs. The archive is updated using the concept of **ε**-dominance, which has the benefit of ensuring that the archive maintains a diverse set of solutions. ε-dominance requires the user to define the precision with which they want to evaluate each objective by specifying an appropriate ε value for each objective. The third step checks if the user-specified performance and termination criteria are satisfied and the Pareto optimal set has been sufficiently quantified. If the criteria are not satisfied, the population size is doubled and the search is continued. When increasing the population, the initial population of the new run has solutions injected from the archive at the end of the previous run. The algorithm terminates if either a maximum user time is reached or if doubling the population size fails to significantly increase the number of nondominated solutions found across two runs.

K. Deb et al. (Eds.): GECCO 2004, LNCS 3103, pp. 390–391, 2004.

3 Results and Conclusions

The efficiency of the proposed algorithm was tested of a suite of two objective test problems that are popular in literature [2]. The parameter settings are set exactly the same as specified by Deb [3], with the exception of the population size. To highlight the algorithms ability to reduce random seed effects, the problems were solved for 50 different random seeds using the same values of ε_i as specified by Deb et al. [3], and the results are presented in Table 1. The performance of the algorithm is measured using the convergence metric described in [3]. All the two objective problems solved by Deb et al. [3] required 20,000 function evaluations to obtain a set of 100 nondominated solutions.

Table 1. The comparison of the results between ε-NSGA-II and ε-MOEA[1] across various performance measures. Reliability is shown in terms of the number of runs that satisfied convergence criteria (α).

Problem	Nfe	No. of Solutions	ε-NSGA-II Convergence	ε-MOEA [see 1] Convergence	Successful runs(α)
ZDT1	5213	95	0.000384836	0.00039545	50(0.01)
ZDT2	5255	96	0.000407489	0.00046448	50(0.01)
ZDT3	5922	97	0.00180699	0.00175135	50(0.01)
ZDT4	8238	93	0.00048264	0.00259063	50(0.01)
ZDT6	8458	93	0.02618	0.067928	50(0.1)
DTLZ2	13842	86	0.045569	0.01080443	48(0.1)

It can be seen from the results that the algorithm required at least 60% fewer function evaluations than prior methods ([2], [3]). Also the algorithm has shown that it has been able to reliably converge to the true Pareto front in more than 96% of the runs.

References

1. Deb, K., *Multi-Objective Optimization using Evolutionary Algorithms*. 2001, New York, NY: John Wiley & Sons LTD.
2. Zitzler, E., K. Deb, and L. Thiele, *Comparison of multiobjective evolutionary algorithms: Empirical results*. Evolutionary Computation, 2000. **8**(2): p. 125-148.
3. Deb, K., M. Mohan, and S. Mishra, *A Fast Multi-objective Evolutionary Algorithm for Finding Well-Spread Pareto-Optimal Solutions*. 2003, Indian Institute of Technology: Kanpur, India.

[1] These results are taken from Deb et al. [3].