The Value of Online Adaptive Search: A Performance Comparison of NSGAII, ε-NSGAII and εMOEA

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Abstract. This paper demonstrates how adaptive population-sizing and epsilon-dominance archiving can be combined with the Nondominated Sorted Genetic Algorithm-II (NSGAII) to enhance the algorithm's efficiency, reliability, and ease-of-use. Four versions of the enhanced Epsilon Dominance NSGA-II (ε-NSGAII) are tested on a standard suite of evolutionary multiobjective optimization test problems. Comparative results for the four variants of the ε-NSGAII demonstrate that adapting population size based on online changes in the epsilon dominance archive size can enhance performance. The best performing version of the ε-NSGAII is also compared to the original NSGAII and the εMOEA on the same suite of test problems. The performance of each algorithm is measured using three running performance metrics, two of which have been previously published, and one new metric proposed by the authors. Results of the study indicate that the new version of the NSGAII proposed in this paper demonstrates improved performance on the majority of two-objective test problems studied.

1 Introduction

Deb *et al.* [1] identified three primary goals in multiobjective (MO) optimization using evolutionary algorithms (EAs): (1) to obtain good convergence toward the Pareto-optimal solution set, (2) to develop a diverse, or evenly distributed set of non-dominated solutions and to maintain this diversity throughout the entire run of the algorithm, and (3) to achieve the first two goals at the lowest computational cost and in the most efficient manner possible. The third goal can be realized through the development of new techniques to achieve convergence and diversity at the lowest possible computational cost and to develop online adaptive EAs that can assess on-line performance and modify key algorithm parameters throughout a run. The ultimate goal of online adaptation is to enhance algorithmic efficiency, reliability, and ease-of-use.

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This study presents alternative techniques by which epsilon-dominance archiving [2], the Nondominated Sorted Genetic Algorithm-II (NSGAII) [3], and parameter adaptation [4] can be combined. These techniques use online performance assessment to adapt population size and to automatically terminate search based on minimal user input and can potentially be integrated into any multiobjective evolutionary algorithm (MOEA) to improve algorithm efficiency, reliability, and ease-of-use. In this paper, section 2 provides a description of the algorithms being compared as well as justification for their selection. Sections 3 and 4 discuss the performance metrics and test problems used in the study. Section 5 presents the results of the simulation in two parts: (1) a comparison of four versions of the ε-NSGAII and (2) a comparison of the best version of the ε-NSGAII identified in the first half of the study to the NSGAII [3] and the εMOEA [1]. Conclusions and potential future research is provided in section 6.

2 Tested Algorithms

The current study is conducted in two parts. The first compares the performance of four versions of the ε-NSGAII, and the second compares the best version of the ε-NSGAII with the NSGAII and the εMOEA.

2.1 Overview of ε-NSGAII

The primary objective of this study is to demonstrate the ε-NSGAII's efficacy at solving multiobjective optimization problems quickly, efficiently, and reliably. The ε-NSGAII is based on the NSGAII, which uses a fast non-dominated sorting approach to classify solutions according to level of non-domination and a crowding distance operator to preserve solution diversity [3]. The ε-NSGAII extends these concepts by adding ε-dominance [2], adaptive population sizing, and self termination to minimize the need for parameter calibration as demonstrated by Reed *et al.* [4].

ε-dominance is a concept whereby the user is able to specify the precision with which they want to obtain the Pareto-optimal solutions to a multiobjective problem, in essence giving them the ability to assign a relative importance to each objective. This is accomplished by applying a grid (sized by user specified ε values) to the search space of the problem. Larger ε values result in a courser grid (and ultimately fewer solutions) while smaller ε values produce a finer grid. The fitness of each solution is then mapped to a box fitness based on the specified ε values. Non-domination sorting is then conducted using each solution's box fitness, and solutions with identical box fitness (i.e., solutions that occur in the same grid block) are compared and those that are dominated within the grid block are eliminated. This results in no more than one non-dominated solution existing in any one grid block, preventing clustering of solutions and promoting a more even search of the objective space. The interested reader can refer to prior work by Laumanns *et al.* [2] and Deb *et al.* [1] for a more detailed description of ε-dominance.

The adaptive population sizing scheme used in the original form of the ε-NSGAII is based on the population sizing theory of Harik *et al.* [5] and the automatic