FastPGA: A Dynamic Population Sizing Approach for Solving Expensive Multiobjective Optimization Problems

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Abstract. We present a new multiobjective evolutionary algorithm (MOEA), called fast Pareto genetic algorithm (FastPGA). FastPGA uses a new fitness assignment and ranking strategy for the simultaneous optimization of multiple objectives where each solution evaluation is computationally- and/or financially-expensive. This is often the case when there are time or resource constraints involved in finding a solution. A population regulation operator is introduced to dynamically adapt the population size as needed up to a user-specified maximum population size. Computational results for a number of well-known test problems indicate that FastPGA is a promising approach. FastPGA outperforms the improved nondominated sorting genetic algorithm (NSGA-II) within a relatively small number of solution evaluations.

Keywords: multiobjective optimization, evolutionary algorithms, Pareto optimality, fast convergence.

1 Introduction

Most real-world problems often involve multiple conflicting objectives, where improving one objective may degrade the performance of one or more of the other objectives. Traditional approaches for solving MOPs typically try to scalarize the multiple objectives into a single objective using a vector of user-defined weights. This transforms the original multiple objective optimization problem formulation into a single objective optimization problem yielding a single solution. Several disadvantages of using such traditional methods have motivated researchers and practitioners to seek alternative techniques to find a set of Pareto optimal solutions rather than just a single solution [2, 3]. A solution is Pareto optimal if there exists no feasible solution for which an improvement in one objective does not lead to a simultaneous degradation in one (or more) of the other objectives. In other words, the solution is a nondominated solution.

1.1 Evolutionary Algorithms for Multiobjective Optimization

Many Pareto-based heuristic search algorithms have been developed to solve MOPs including simulated annealing, tabu search, scatter search, and evolutionary algorithms

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(EAs). EAs, the focus of this study, are population-based stochastic search algorithms inspired by Darwinian evolutionary theory (*i.e.*, the survival of the fittest). It has been shown that EAs are able to balance exploration and exploitation of the solution search space [6].

Several variations of multiobjective evolutionary algorithms (MOEAs) have been developed to handle MOPs [2, 3]. Many of the suggested MOEAs have been employed in a variety of real-world applications [1]. Among the existing algorithms, an improved version of the nondominated sorting genetic algorithm (NSGA-II) of Deb *et al.* [4], a newer version of strength Pareto EA (SPEA2) of Zitzler *et al.* [14], an improved version of multiobjective messy GA (MOMGA) of Zydallis *et al.* [16], and Pareto-archived evolution strategy (PAES) of Knowles and Corne [8] are the more popular MOEAs. Given the variations of MOEAs, the idea of using dynamic population sizing has not been thoroughly investigated, and to date only a few studies have explored this idea. For example, Tan *et al.* [9] introduce an incrementing MOEA that uses dynamic population sizing based on the online discovered Pareto front and its desired population distribution density. In another study, Yen and Lu [12] propose a dynamic MOEA, called DMOEA, which incorporates cell-based rank and density estimation strategy to efficiently compute dominance and diversity information when the population size varies dynamically.

After developing many effective MOEAs for solving inexpensive MOPs, there is now a growing need for designing MOEAs capable of dealing with expensive MOPs in that there are computational and financial resource constraints. Few multiobjective optimization algorithms exist for expensive MOPs. Most recently, Knowles [7] introduces a hybrid algorithm with online landscape approximation, called ParEGO, for expensive MOPs where only 100 and 250 solution evaluations are permitted.

1.2 Purpose of Research

In many previous real-world applications of MOEAs, the time to perform a single solution evaluation is typically of the order of minutes or even hours resulting in a limited number of solution evaluations that can be performed. This is especially relevant when implementation of the discovered solutions is time-sensitive. Additionally, many real-world problems involve complicated objective functions making a large number of solutions evaluations computationally-prohibitive [7]. Specifically, our motivation comes from simulation-based optimization research. Computer simulation of real-world systems tend to involve construction of complicated models that capture the complex, nonlinear interrelationships between independent and dependent variables and can report the value of several system performance objectives simultaneously. These models are used to evaluate candidate system design solutions in search of the best solution (or set of solutions) according to several performance objectives. A multiobjective optimization algorithm capable of rapidly finding a diverse set of Pareto optimal solutions would be greatly beneficial in such a situation. The purpose of this research is to propose a multiobjective optimization methodology that finds evenly-distributed Pareto optimal solutions in a computationally-efficient manner.

The remainder of this paper is organized as follows. Section 2 describes the proposed MOEA. This description includes the introduction of a new fitness assignment