DEMO: Differential Evolution for Multiobjective Optimization

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Abstract. Differential Evolution (DE) is a simple but powerful evolutionary optimization algorithm with many successful applications. In this paper we propose Differential Evolution for Multiobjective Optimization (DEMO) – a new approach to multiobjective optimization based on DE. DEMO combines the advantages of DE with the mechanisms of Pareto-based ranking and crowding distance sorting, used by state-of-the-art evolutionary algorithms for multiobjective optimization. DEMO is implemented in three variants that achieve competitive results on five ZDT test problems.

1 Introduction

Many real-world optimization problems involve optimization of several (conflicting) criteria. Since multiobjective optimization searches for an optimal vector, not just a single value, one solution often cannot be said to be better than another and there exists not only a single optimal solution, but a set of optimal solutions, called the *Pareto front*. Consequently, there are two goals in multiobjective optimization: (i) to discover solutions as close to the Pareto front as possible, and (ii) to find solutions as diverse as possible in the obtained nondominated front. Satisfying these two goals is a challenging task for any algorithm for multiobjective optimization.

In recent years, many algorithms for multiobjective optimization have been introduced. Most originate in the field of Evolutionary Algorithms (EAs) – the so-called Multiobjective Optimization EAs (MOEAs). Among these, the NSGA-II by Deb et al. [1] and SPEA2 by Zitzler et al. [2] are the most popular. MOEAs take the strong points of EAs and apply them to Multiobjective Optimization Problems (MOPs). A particular EA that has been used for multiobjective optimization is Differential Evolution (DE). DE is a simple yet powerful evolutionary algorithm by Price and Storn [3] that has been successfully used in solving single-objective optimization problems [4]. Hence, several researchers have tried to extend it to handle MOPs.

Abbass [5, 6] was the first to apply DE to MOPs in the so-called Pareto Differential Evolution (PDE) algorithm. This approach employs DE to create

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new individuals and then keeps only the nondominated ones as the basis for the next generation. PDE was compared to SPEA [7] (the predecessor of SPEA2) on two test problems and found to outperform it.

Madavan [8] achieved good results with the Pareto Differential Evolution Approach (PDEA[1]). Like PDE, PDEA applies DE to create new individuals. It then combines both populations and calculates the nondominated rank (with Pareto-based ranking assignment) and diversity rank (with the crowding distance metric) for each individual. Two variants of PDEA were investigated. The first compares each child with its parent. The child replaced the parent if it had a higher nondominated rank or, if it had the same nondominated rank and a higher diversity rank. Otherwise the child is discarded. This variant was found inefficient – the diversity was good but the convergence slow. The other variant simply takes the best individuals according to the nondominated rank and diversity rank (like in NSGA-II). The latter variant has proved to be very efficient and was applied to several MOPs, where it produced favorable results.

Xue [9] introduced Multiobjective Differential Evolution (MODE). This algorithm also uses the Pareto-based ranking assignment and the crowding distance metric, but in a different manner than PDEA. In MODE the fitness of an individual is first calculated using Pareto-based ranking and then reduced with respect to the individual's crowding distance value. This single fitness value is then used to select the best individuals for the new population. MODE was tested on five benchmark problems where it produced better results than SPEA.

In this paper, we propose a new way of extending DE to be suitable for solving MOPs. We call it DEMO (Differential Evolution for Multiobjective Optimization). Although similar to the existing algorithms (especially PDEA), our implementation differs from others and represents a novel approach to multiobjective optimization. DEMO is implemented in three variants (DEMO/parent, DEMO/closest/dec and DEMO/closest/obj). Because of diverse recommendations for the crossover probability, three different values for this parameter are investigated. From the simulation results on five test problems we find that DEMO efficiently achieves the two goals of multiobjective optimization, i.e. the convergence to the true Pareto front and uniform spread of individuals along the front. Moreover, DEMO achieves very good results on the test problem ZDT4 that poses many difficulties to state-of-the-art algorithms for multiobjective optimization.

The rest of the paper is organized as follows. In Section 2 we describe the DE scheme that was used as a base for DEMO. Thereafter, in Section 3, we present DEMO in its three variants. Section 4 outlines the applied test problems and performance measures, and states the results. Further comparison and discussion of the results are provided in Section 5. The paper concludes with Section 6.

[1] This acronym was not used by Madavan. We introduce it to make clear distinction between his approach and other implementations of DE for multiobjective optimization.