# Differential Evolution Versus Genetic Algorithms in Multiobjective Optimization

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**Abstract.** This paper presents a comprehensive comparison between the performance of state-of-the-art genetic algorithms NSGA-II, SPEA2 and IBEA and their differential evolution based variants DEMO$^{\text{NS-II}}$, DEMO$^{\text{SP2}}$ and DEMO$^{\text{IB}}$. Experimental results on 16 numerical multiobjective test problems show that on the majority of problems, the algorithms based on differential evolution perform significantly better than the corresponding genetic algorithms with regard to applied quality indicators. This suggests that in numerical multiobjective optimization, differential evolution explores the decision space more efficiently than genetic algorithms.

## 1 Introduction

Differential Evolution (DE) [1] is a simple yet powerful algorithm that outperforms Genetic Algorithms (GAs) on many numerical singleobjective optimization problems [2]. In this paper we show that DE can achieve better results than GAs also on numerical multiobjective optimization problems (MOPs). To this end, we compare three state-of-the-art Multiobjective Evolutionary Algorithms (MOEAs), namely NSGA-II [3], SPEA2 [4] and IBEA [5], to their counterparts – algorithms that use the same environmental selection, but DE instead of GAs for exploring the decision space. While DE-based algorithms for multiobjective optimization have already been proposed in the past (see Related Work in Section 3), comparisons between these approaches and GA-based algorithms lack: (a) a wide choice of difficult test problems with more than two objectives, (b) performance assessment with Pareto compliant indicators, and (c) inferences about algorithm performance based on statistical tests. The comparison in this paper includes all these usually omitted features.

The paper is further organized as follows. Section 2 introduces the basic GA as the underlying algorithm for NSGA-II, SPEA2 and IBEA, while the proposed algorithm DEMO is explained in detail in Section 3. Section 4 outlines the experiments, whose results are presented and discussed in Section 5. Section 6 concludes the paper with a summary of the results.

## 2 Multiobjective Optimization with the Basic GA

Most of the efforts spent on adapting GAs to multiobjective optimization have been focusing on finding new approaches for environmental selection. These

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approaches try to produce good approximations of the Pareto optimal front by incorporating different preferences. For example, the environmental selection in NSGA-II [3] first ranks the individuals using nondominated sorting. To distinguish between individuals with the same rank, the crowding distance metric is used, which prefers individuals from less crowded regions of the objective space. SPEA2 [4] works similarly, calculating the raw fitness of the individuals according to Pareto dominance relations between them and using a density measure to break the ties. The individuals that reside close together in the objective space are discouraged from entering the archive of best solutions. IBEA [5], on the other hand, uses a different approach. The fitness of individuals is determined only according to the value of a predefined indicator. This indicator has to be dominance preserving and no other explicit diversity preserving mechanism (such as crowding in NSGA-II or density in SPEA2) is applied.

While directing all attention to environmental selection, the popular algorithms NSGA-II, SPEA2 and IBEA use practically the same algorithm for exploring the decision space. It is therefore possible to describe all three algorithms using a unifying framework, which will be called *Basic Genetic Algorithm* in the remainder of this paper. This algorithm is presented in Fig. 1. After initialization of the populations $\mathcal{P}$ and $\mathcal{Q}$, which is slightly different in NSGA-II, SPEA2 and IBEA[1], the evolutionary steps of selection, crossover and mutation are repeated until a stopping criterion is met. In environmental selection, one of the previously described approaches is used to calculate the fitness of the individuals. This fitness is used again when comparing individuals in tournament selection. Figure 2 shows the variation operators on individuals encoded as real vectors. In case of combinatorial MOPs, different operators need to be used.

**Basic Genetic Algorithm for Multiobjective Optimization**

1. Initialize populations $\mathcal{P}_0$ and $\mathcal{Q}_0$.
2. Set $t = 0$.
3. Repeat:
   3.1. Set $t = t + 1$.
   3.2. Calculate the objectives for new individuals from $\mathcal{P}_{t-1}$ and $\mathcal{Q}_{t-1}$.
   3.3. Get $\mathcal{P}_t$ from $\mathcal{P}_{t-1}$ and $\mathcal{Q}_{t-1}$ with environmental selection.
   3.4. If stopping criterion met, return nondominated individuals from $\mathcal{P}_t$.
   3.5. Fill the mating pool $\mathcal{M}_t$ using tournament selection on $\mathcal{P}_t$.
   3.6. Apply variation to individuals from $\mathcal{M}_t$ to get $\mathcal{Q}_t$ (see Fig. 2).

**Fig. 1.** Outline of the basic genetic algorithm

[1] While NSGA-II initializes the population $\mathcal{P}_0$ with randomly created individuals and sets $\mathcal{Q}_0$ to be empty, in SPEA2, $\mathcal{P}_0$ represents the archive of best solutions and is therefore initially empty, while $\mathcal{Q}_0$ is filled with randomly created individuals. IBEA originally uses a single population of variable size instead of two separate populations. Without altering its performance, we can assume that IBEA uses two populations, which are initialized in the same way as in NSGA-II.