On a Restart Metaheuristic for Real-Valued Multi-Objective Evolutionary Algorithms

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ABSTRACT

Incorporating a restart operator into a multi-objective evolutionary algorithm (MOEA) yields its performance improvement. Restarting an algorithm aims at preventing stagnation and reaching solutions uniformly distributed along the whole Pareto front. The presented experimental results for two MOEAs with the restart operator demonstrate vast potential of this metaheuristic. The use of the restart operator is limited by the necessity to adjust its key parameters for the problem solved.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence → Search methodologies**

KEYWORDS

Restart operator, metaheuristic, multi-objective optimization, performance improvement

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1 INTRODUCTION

A concept of restarting a search algorithm has been developed mostly for one-criterion heuristics to avoid stagnation and let an algorithm leave attraction basins of local optima [1]. In multi-objective optimization, a restart operator is also helpful in exploring new regions of the search space and obtaining uniformly distributed trade-off solutions along the true Pareto front [2]. As opposed to conventional operators (selection, crossover, mutation), which are applied at each generation, the restart operator is used either according to a predefined schedule (in every *k* generations) or when a specified criterion is satisfied. The latter approach, namely a *dynamic* restart, examines the algorithm behavior on a problem solved and applies the restart operator when it is needed [3].

In this study, we develop an algorithm independent restart operator which is applicable for different Multi-Objective Evolutionary Algorithms (MOEAs). The proposed restart metaheuristic has been incorporated into two real-valued MOEAs (Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D)) and tested on the CEC2009 test problems.

2 RESTART OPERATOR

The proposed restart operator consists of three components. The first component collects the data that represents the algorithm behavior, the second one evaluates metrics and checks whether they reach defined thresholds, and the third component creates a new population.

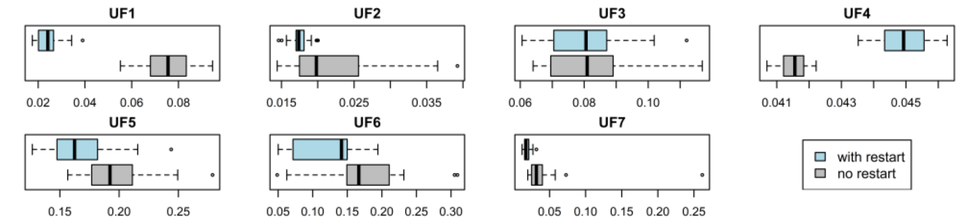

Figure 1: NSGA-II performance with and without the restart on the set of unconstrained two-objective optimization problems.

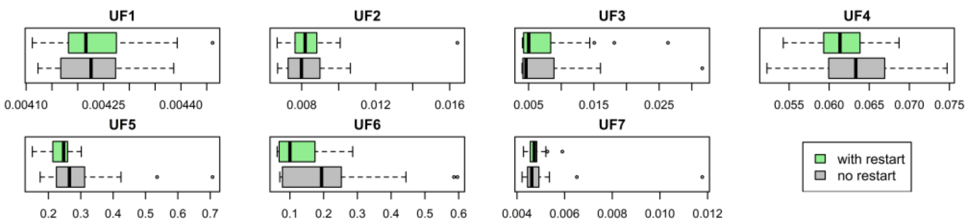

Figure 2: MOEA/D performance with and without the restart on the set of unconstrained two-objective optimization problems.

Since there is a need in estimating stagnation, we evaluate the distance between Pareto front estimations (non-dominated solutions) for each pair of consequent populations. Let $\hat{F}_i^P, i = \overline{1, n}$ be the Pareto front estimation of the i-th population, where n is the number of generations. The difference between Pareto front estimations is evaluated as follows:

$$D_i^P = d\left(\hat{F}_{i+1}^P, \hat{F}_i^P\right), i = \overline{1, n-1}, \quad (1)$$

where $d\left(\hat{F}_{i+1}^P, \hat{F}_i^P\right) = \left|\hat{F}_{i+1}^P\right|^{-1} \sum_{j=1}^{\left|\hat{F}_{i+1}^P\right|} \min_{x_k \in \hat{F}_i^P} \left\| \left(\hat{F}_{i+1}^P\right)_j - x_k \right\|$ is the distance between the front estimations and $\left|\hat{F}_{i+1}^P\right| = card\left(\hat{F}_{i+1}^P\right)$. The restart operator is applied at the j-th generation, if

$$D_k^P \leq \delta_P, \forall k : i - \tau_P \leq k \leq i\,, \quad (2)$$

where δ_P is the threshold and τ_P is the number of generations to be examined. Condition 2 is met, when for τ_P previous generations, distances D_k^P between Pareto front estimations found by the algorithm do not exceed δ_P. When the restart operator is applied, firstly, the current population is copied to the storage and, secondly, a new population is generated. In this study, stored solutions are not used to create a new population, only to form the final Pareto front estimation.

3 EXPERIMENTS AND RESULTS

The performance of real-valued NSGA-II and MOEA/D [4] was investigated on the set of unconstrained two-objective problems CEC2009. Experiments were made according to the rules of this competition [5]. The IGD metric was evaluated to compare performance of MOEAs. For the restart operator, different combinations of parameter values were tested: $\delta_P = 0.1$, 0.05, 0.01, 0.005, 0.001; $\tau_P = 5$, 10, 15, 20, 25. The highest IGD values achieved with restarting are shown in Figures 1 and 2. The proposed metaheuristic allowed us to decrease the IGD values or keep the same level for many test problems. Only for problem 4, original NSGA-II outperformed its version with the restart.

4 CONCLUSIONS

In this study, we demonstrate positive effects of restarting in multi-objective optimization. The use of the restart operator has potentials to increase the MOEA performance. Meanwhile, its application involves the restart parameters tuning, which becomes non-trivial when the number of objectives increases (e.g. CEC2009 problems with three and more criteria). Therefore, the further studies are focused on modifying this operator to make it adaptive for different optimization problems and search algorithms. One more related issue is the way to generate a new population using the data collected during the search.

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