MOEAs on Problems with Difficult Pareto Set Topologies

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1 Introduction

We study the performance of two well-established dominance-based MOEAs, namely NSGA-II and AεSεH, when solving a set of MOPs with difficult Pareto set (PS) topology. Mainly, we focus on the ZCAT test problems since, in our judgment, they involve a vast number of elements that could be contained in real-world problems. The experimental study presented in this work, shows some interesting and useful conclusion to understand better dominance-based MOEAs which is the principal focus of this work.

2 Algorithms and Experimental Setup

In this study, four different algorithm configurations are compared: NSGA-II-SBX, NSGA-II-DE, AεSεH-SBX, and AεSεH-DE. An adaptation of Differential Evolution (DE) was implemented to use it as a crossover operator, so the traditional steady state replacement of DE was substituted for a generational replacement compatible with both algorithms.

In total, 2 from all 20 ZCAT problems were tested, namely ZCAT3 and ZCAT8, with Unimodal & Separable instances. The number of objectives m = 2 and set the total number of variables to n = 20.

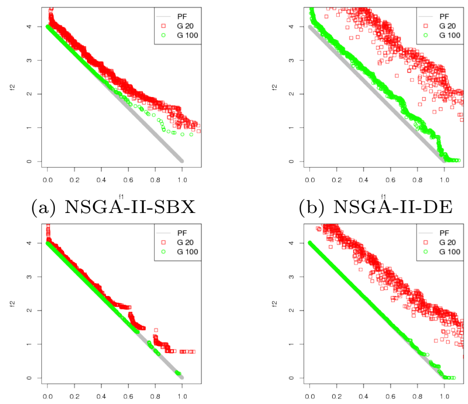
We run each algorithm 30 times using the same set of seeds. The maximal number of generations is set 100 for unimodal problems. Crossover settings are $p_c = 1.0$, $p_{cv} = 0.5$, and mutation rate is $p_m = 1/$n. When DE operator was used, F = 0.5. In case of SBX crossover, $\eta_c = 15$. In both cases, polynomial mutation is set to $\eta_m = 20$. Population size is set to $|\mathcal{P}| = 1000$, and the reference neighborhood size for AεSεH is set to 20 individuals.

3 Experimental Results and Discussion

In this work, we carefully evaluate algorithms performance using unimodal/separable ZCAT problems.

Figure 1 presents results for the best run of each algorithm in terms of hypervolume value. By analyzing the results, there is a trade-off between algorithms using SBX and DE, while SBX produces a faster convergence towards the Pareto Front (PF), DE is capable of finding better distributed solutions in detriment of convergence. This conclusion can be verified by comparing NSGA-II-SBX and NSGA-II-DE.

Results suggest that neighborhood parent selection may increase convergence of solutions. When comparing algorithms NSGA-II-SBX and AεSεH-SBX, solutions produced by AεSεH are closer to the PF than NSGA-II for the same generation. This faster approach to the PF may lead AεSεH to shift the search from convergence stage to diversity stage, producing a better distributed set of solutions. When comparing the size of first front, AεSεH-SBX reaches a number equal to the population size faster than NSGA-II-SBX. As pointed out in [1], this can be an indicator for phase transition between conversion to distribution. Therefore, the algorithm can produce a better coverage of PF as it is operating in diversity stage.



(a) NSGA-II-SBX (b) NSGA-II-DE
(c) AεSεH-SBX (d) AεSεH-DE

Figure 1: Population from the best run of each algorithm over ZCAT8 unimodal instance.

4 Conclusion

Neighborhood parent selection in objective space can produce an improvement on the convergence of solutions, contributing to a faster transition from dominance-based stage to diversity-based, and by consequence improving algorithm PF coverage. Another finding is that differential evolution operator can improve the search ability of the algorithms by finding solutions better distributed across the objective space.

References

[1] Hernán Aguirre, Yuki Yazawa, Akira Oyama, and Kiyoshi Tanaka. Extending *aεsεh* from many-objective to multi-objective optimization. In *Proceedings of 10th International Conference on Simulated Evolution and Learning*, pages 239–250, Dec. 2014.