Controlled Local Search for the Hybridization of Evolutionary Algorithms in Multi-Objective Optimization

A. Haidine, A. Aqqal and S. El Hassani

Laboratoire de Technologies de l'Information (LTI)
Ecole Nationale des Sciences Appliquées- El Jadida (ENSA-J)
Université Chouaib Doukkali
24002 El Jadida, Morocco
abdel.haidine@gmail.com

Keywords: Multi-Objective Optimization, Local Search, Hybrid Algorithms, Multi-Objective Evolutionary Algorithms (MOEA).

1 Introduction

The idea to hybridize the evolutionary algorithms by the local search has received interest firstly in the Single-Objective Optimization (SOO) field. Then, this idea has been taken into the Multi-Objective Optimization (MOO) over, to build the hybrid MOEA. The main advantage of using the hybridization is the improvement in the convergence to the (global) Pareto front. However, this has a main drawback, which is the increase of the computation time. From this hybridization, two main variants have resulted. The first main variant has been implemented by [1] and called Multi-Objective Genetic Local Search (MOGLS) algorithm, where a scalar fitness with random weights is used for the selection of the parents and the local search for their offspring. This algorithm has been improved by modifying its selection mechanism of parents in [Jas02]. Despite that this has been improved, MOGLS is still using the scalar fitness function with random weights in selection and local search, it does not use the roulette wheel selection over the entire population. A pair of parents is randomly selected from a pre-specified number of the best solutions with respect to the scalar fitness function with the current weights. This selection scheme can be seen as a kind of mating restriction in MOEA. The second main variant is called Memetic Pareto Archived Evolutionary Strategy (M-PAES). This uses a kind of evolutionary strategy called (1+1)-PAES to execute the local search; [2]. In the above-mentioned hybrid MOEAs, local search was applied to individuals in every generation. In other studies, local search was applied to individuals only in the final generation; [3].

The hybridization of MOO, which is proposed in this paper, has three specific characteristics: *(i)* the evolutionary search is based on the Pareto MOEA (i.e. NSGA, NSGA-II, SPEA, SPEA-2 and SPEA2+); *(ii)* local search does not use objective scaling, instead it uses a Multi-Objective Local Search in two different forms (diversity-MOLS to have large-sized Pareto front and convergence-MOLS to come closer to optimal Pareto front); and *(iii)* different hybridization techniques are discussed/implemented and evaluated.

2 Hybridization Approaches

Different hybridization schemes from SOO can be used in the MOO; for example, the component hybridization. The hybrid of Pareto MOEA with MOLS works similarly to Guided Evolutionary Simulated Annealing (GESA). Also the principle of Parallel Recombinative Simulated Annealing (PRSA) can be applied to build Annealed MOEA. Such variants are neither proposed nor investigated in any of MOO literature. The component hybrid MOEA variants are not investigated here. In this work, we focus on the technique hybridization of the Pareto-based MOEAs. Unlike the MOGLS, the hybridization will be done without use of scaling weights of the objectives; rather it will be done by the means of the Multi-Objective Local Search (MOLS). The hybridization is done according to two different schemes; either in a sequential way (executing MOEA and resulting Pareto is submitted to LS) or in an incorporated manner; where LS is applied to all population of MOEA. The MOLS can be controlled by adapting the acceptance probability, to either push optimization to more large-sized Pareto fronts to reach very diversified non-dominated final solution; or to orient the search to go closer to global optimum Pareto front; Figure 1.

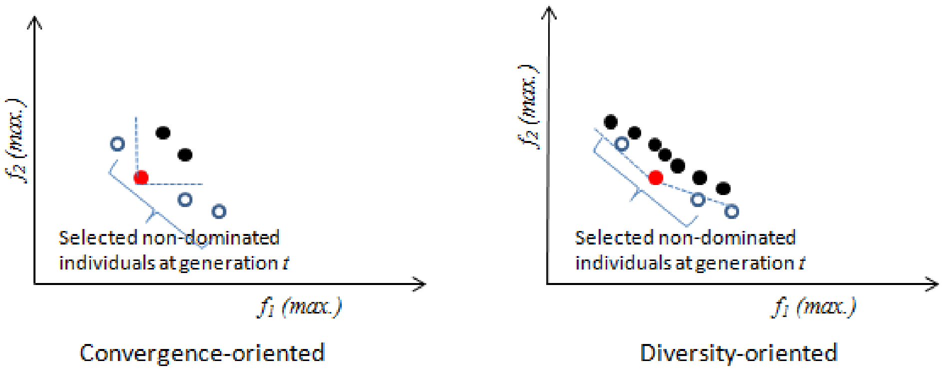

Figure 1: Controlled MOLS to either force optimization to Pareto front diversity (div-LS, *right*), or better convergence (conv-LS, *left*)

3 Numerical Results (*initial samples*)

For the evaluation of the proposed hybridization approaches, the algorithms have been applied to solve three benchmarks of the 0/1 Multi-Objective Knapsack Problem (MOKP); which is defined as follows (taking $k=2$ to have a simplified 2-dimensional MOO; and three scenarios: with 250, 500 and 750 items):

Given:	A set of n items and a set of k knapsacks (KS), with $p_{i,j}$: profit (or gain) of item j according to knapsack i; $w_{i,j}$: weight of item j according to knapsack i, and C_i: capacity of KS i;
Task:	Find a vector $\mathbf{x} = (x_1, x_2, \ldots, x_n) \in \{0, 1\}^n$;
Objective:	*maximize* $\mathbf{f}(\mathbf{x}) = [\ f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})\ ]$
Such that:	$f_i = \sum_{j=1}^{n} p_{i,j}.x_j;\ \ p_{i,j} = \begin{cases} 1, & item\ j\ in\ KS\ i \\ 0, & otherwise \end{cases}$; and $\sum_{j=1}^{n} w_{i,j}.p_{i,j}.x_j \leq C_i$.

The simulation results show clear improvement in the performance of the evolutionary algorithms. A sample of delivered optimization output is presented in Fig. 2; (more results will be in full-version paper).

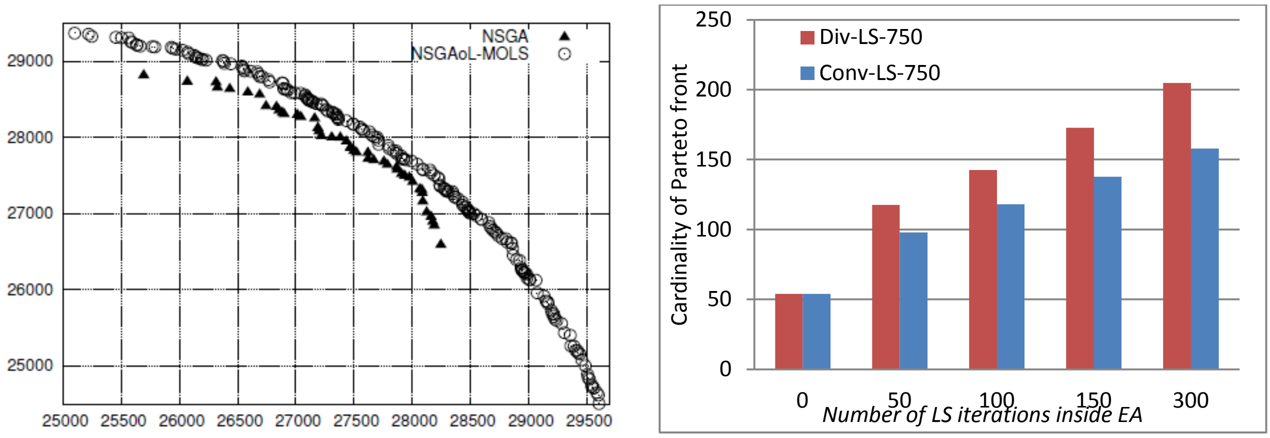

Figure 2: Pareto fronts from MOEA only (e.g. NSGA) and the hybrid version by incorporated LS; using diversity-LS (*left*); and its comparison to the convergence-oriented LS (*right*) for MOKP-750.

References

[1] H. Ishibuchi and T. Murata:"*A multi-objective genetic local search algorithm and its application to flow-shop scheduling*," IEEE Trans. on Sys., Man., and Cybernetics, 28(3):392-403, August 1998.

[2] J. D. Knowles: *Local-Search and Hybrid Evolutionary Algorithms for Pareto Optimization*. PhD Thesis, Department of Computer Science, University of Reading, Reading, UK, January 2002.

[3] K. Deb and T. Goel: "*A hybrid multi-objective evolutionary approach to engineering shape design*," in Proc. of the 1st Int. Conf. on Evolutionary Multi-Criterion Optimization, pp. 385-399, Switzerland, 2001.