MEMOX: a Memetic Algorithm Scheme for Multiobjective Optimization

Thibaut Lust* Jacques Teghem*

*MATHRO, Faculté Polytechnique de Mons
9, rue de Houdain — B7000 Mons, Belgium
thibaut.lust@fpms.ac.be

1 Overview of memetic algorithms for multiobjective optimization

A memetic algorithm (or genetic local search) is a genetic algorithm where the mutation operator is replaced by a local search method applied to every new offspring generated [9]. The memetic algorithms are particularly well adapted to the resolution of multiobjective optimization problems since a set of diversified solutions (from which the interest of using a population) but also close to the Pareto front (what is ensured by the local search) is required.

In an interesting survey of memetic algorithms for multiobjective optimization [8], Knowles and Corne distinguish three principal groups of authors who developed memetic multiobjective algorithms: Ishibuchi and Murata with the IMMOGLS (Ishibuchi Murata MultiObjective Genetic Local Search) method [2], Jaszkiewicz with the MOGLS (MultiObjective Genetic Local Search) [5] and PMA (Pareto Memetic Algorithm) [4] methods and Knowles and Corne with the M-PAES (Memetic Pareto Archived Evolution Strategy) method [7].

The three methods IMMOGLS, MOGLS and PMA are all based on the same principle: they use a scalarizing function, defined thanks to a weight vector randomly drawn, to select probabilistically two parents being good on this function. The two parents are then recombined, to generate an offspring. The local search is applied to the offspring and finally, the improved offspring competes with the population for survival to the next generation. The only point on which the three algorithms differs is the choice of the parents used for the recombination. The M-PAES method is rather different from the three preceding ones, since none scalarizing function is used, either in the local search or the parents selection. The solutions evaluation is instead based on a form of Pareto Ranking. The local search is the (1+1)-PAES method [6], which uses a hypergrid for maintaining a finite size archive of non-dominated solutions. A crossover operator is employed periodically to recombine the solutions found by the (1+1)-PAES procedure.

We present in this paper a new multiobjective memetic algorithm scheme, called MEMOX, that combines elements of the algorithms presented here, without using scalarizing functions.

2 The MEMOX scheme

The algorithm scheme, presented at figure 1 is as follows. In an initialization phase, a certain local search method X is applied from an initial solution randomly generated. The local search method can be any multiobjective method functioning with a neighborhood, like hill-climbing, tabu search or simulated annealing. In this initialization phase, the aim of the local search is to provide at least $r+1$ non-dominated solutions (also called potentially efficient solutions). The role of this parameter is explained after. The potentially efficient solutions found by this initialization phase represent the initial population. Then, as in MOGLS, two solutions from the population are selected. The first selected solution, called X_1, is one of the solutions of the population having a minimal density, calculated thanks to a division of the objectives space in hypervolumes. This is the main difference with respect to the other memetic algorithms. The technique employed to realize this division is explained at section 3. The second one, called X_2, is one of the solutions among the r closest [3] to the first solution according to the euclidean distance in the objectives space. This is why it is necessary to generate at least $r+1$ potentially efficient solutions during the initialization phase. We combine then the both solutions X_1 and X_2 by using a crossover operator for thus obtaining a new solution called X_3. We apply again the local search method from X_3 until no more improvement in the solutions set happens during a certain iterations number it_{stop}. Finally, this process is reiterated by again selecting the minimal density solution.

The role of the local search is to intensify the research by generating new solutions close to the selected solution of minimal density X_1. The diversification of the method is ensured by the improvement of solutions of minimal density, which makes it possible to generate new solutions in little or not exploited zones. An important parameter of the MEMOX scheme is the it_{stop} parameter, i.e. after how many iterations without improvement we have to stop the local search, knowing that the total number of iterations is limited. It can thus be preferable to start again the local search from a solution of minimal density rather than to strongly intensify in a precise zone.

3 The dynamic hypergrid

The role of the hypergrid is to measure the density of the solutions. The hypergrid is created by a division of the objectives space in hypervolumes. The density of a solution is thus defined by the number of solutions being in the same hypervolume as the solution. The hypergrid size has to be managed, because if the number of hypervolumes that compose the hypergrid is to high, all the solutions will be on different hypervolumes. On the other hand, if there are not enough hypervolumes, a lot of solutions will be on the same hypervolumes.

That is why the number of hypervolumes is dynamically updated. As the method starts from a low number of solutions and this number is for the majority of the cases in constant increases, we also constantly increase the number of divisions of the hypergrid. The rule is as follows: if the average density of the solutions becomes higher than a certain value, we increase by a certain step the number of divisions of the hypergrid. In this way, we guarantee a good measure of density. The hypergrid is also updated as soon as a new solution being apart from the hypergrid has been generated. Between each update, we keep in memory the hypergrid

Parameters

it_{stop}: iterations number of the local search without improvement
r: number of solutions taken into account for the selection of the closest solution
n: maximum number of iterations

Notations

i: current iterations number
n_{ls}: counter of the iterations number of the local search
$PE \equiv$ list of non-dominated solutions, potentially efficient
$|PE|$: number of potentially efficient solutions
$D(X) \equiv$ density of a potentially efficient solution X

Initialization

$i \leftarrow 0$
Choose randomly a feasible solution X_0
$PE \leftarrow PE \ + \{X_0\}$
$X_3 \leftarrow X_0$

Iteration i

Apply a local search method X from X_3 until no more improvement in PE while it_{stop} and $|PE| > r$
$i \leftarrow i + n_{ls}$
For each solution of PE calculate the density $D(X_l) \ \ l = 1, \ldots, |PE|$
Calculate $D^* = D(X_p{}^*) = \min\limits_{l=1,\ldots,|PE|} D(X_l) \ p = 1, \ldots, P$ ($P > 1$ in case of ex æquo)
Choose randomly a solution X_1 among $\{X_p{}^*, p = 1, \ldots, P\}$
Choose a solution X_2 among the r solutions of PE closest to X_1
Cross the two solutions X_1 and X_2 for obtaining X_3
$PE \leftarrow PE \ + \{X_3\}$
Actualize PE (to keep only the non-dominated solutions)

Stop Criterion

Iteration count $i = n$

Figure 1: MEMOX scheme

and the solutions density, which makes it possible to reduce the computational time.

4 Experimentations on the knapsack problem

We experiment the MEMOX scheme on the multidimensional multiobjective knapsack problem. The local search method used is an original Tabu Search method called PRTS (Pareto Ranking Tabu Search) which uses an evaluation based on the Double Pareto Ranking [1], which leads to the MEMOTS method. We use different quality indicators (hypervolume, average and maximum distance to a reference set, percentage of efficient solutions found, etc.) to evaluate the performances of the method and we show different things :

- The selection of minimal density solutions for the crossover operator gives better results than a random selection, essentially for the diversification propriety.
- The parameters of the dynamic hypergrid, making it possible to measure the density of the solutions, are relatively easy to fix, and this technique could be easily integrated in other multiobjective algorithms.
- The more the number of objectives increases, the more the need for an advanced local search method in the MEMOX scheme is weak.

Finally, the results of MEMOTS are compared to other memetic algorithms (MOGLS, IMMOGLS and PMA) and they are globally of better qualities.

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