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A Fast Local Search Approach For Multiobjective problems *

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Abstract. In this article, we present a new local method for multiobjective problems. It is an extension of local search algorithms for the single objective case, with specific mechanisms used to build the Pareto set. The performance of the local search algorithm is illustrated by experimental results based on a real problem with three objectives. The problem is issued from electric car-sharing service with a car manufacturer partner. Compared to the Multiobjective Pareto Local Search (PLS) well known in the scientific literature [1], the proposed model aims to improve: the solutions quality and the time computing.

Keywords: Local search algorithm - Multiobjective optimization - Transportation services - Car-sharing

1 Introduction

Many real world problems require to optimize several objectives simultaneously, they are called multiobjective optimization problems (MOP). When it does not exist a unique solution optimizing all objectives in an optimal way, we need to find other decisional mechanisms. The Pareto dominance is one of these; for MOP, the Pareto set is composed of all best compromises between the different objectives. The Pareto set is achieved if there are no other dominant solutions in the search space. The Pareto front is defined as the image of the Pareto set in the objective space [2]. In the past few years, a lot of works were based on multiobjective evolutionary algorithms (MOEA) such NSGA-II[3] , SPEA [4] and SPEA2 [5], sometime coupled with local search in memetic approaches [6][7].

To solve single objective combinatorial optimization problems, local search algorithms provide often efficient metaheuristics. They can also be adapted to multiobjective combinatorial problems like in Pareto Local Search algorithm (PLS) [1] with a complete exploration of the neighborhood, or with strategy based on the neighborhood structure [8]. A recent work has been done to unify local search algorithms applied to MOP, known as Dominance-based Multiobjective Local Search (DMLS) [9]. Finally, some algorithms add a Tabu criteria in the local search [10][11].

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The local search approach we propose, named FLS-MO, is based on the Pareto optimality. A neighbor is acceptable if and only if it is not dominated by the solutions found so far. This criteria was used in other approaches as in [1] but the originality of our method is to be very intensive while maintaining a good diversity. With this new tradeoff between intensification and diversification we get good results in comparison with PLS.

2 Fast Local Search for Multiobjective problems

The new algorithm is based on a not dominated local search. The initial solution is build randomly, marked as not explored and added to the solutions set. While it exists a not explored solution in the solutions set, the algorithm chooses randomly such a solution and use it recursively until being in a local optimum. At each step the first random neighbor that provides a new non-dominated solution is accepted. The algorithm stops when all non-dominated solutions are marked as explored. The result is an approximation of the Pareto set. The approach combines two qualities: a good intensification based on exploration of any non-dominated solution of the set and a good diversification because all non-dominated solutions are accepted in the set.

Algorithm 1 Fast Local Search for Multiobjective Problems

$S \leftarrow$ init() {init the solution set S with a random individual}
$s \leftarrow$ select(S) {select randomly a not explored solution from S}
while $s \neq \emptyset$ **do**
  repeat
    $s' \leftarrow$ selectNeighbor(s) {select randomly a neighbor of s not dominated by S}
    if $s' \neq \emptyset$ **then**
      $s \leftarrow s'$
      addNotDominated(s) {add s in S and remove all dominated solutions}
    end if
  until $s' = \emptyset$
  mark s as explored
  $s \leftarrow$ select(S) {select randomly a not explored solution from S}
end while

3 Study Case: charging stations location for electric car-sharing service

Car-sharing services was first experimented in 1940 [12]. To deploy the service, we need to locate charging stations where the people take and return the cars. In our case, it is not necessary to return the vehicle in its starting station. Solving approaches based on exact methods already exist such as [13] but they consider simplified problem. We have applied FLS-MO algorithm to approximate the

Pareto set of this problem. The aim is to locate n stations in a given area to maximise several daily requests of population flows.

The area is discretized into a grid and all the flows are set in a 3D matrix $F = (f_{i,j,t})$ where $f_{i,j,t}$ represents the number of displacements from the cell i to the cell j at time period t. We have 3 objectives to locate the charging stations:

f1 : flow maximization i.e. the locations must allow us to maximize the flows between themselves

$$f_1 = \max_{s \in \Omega} \left[\sum_{st_i \in s} \sum_{st_j \in s \setminus \{st_i\}} f(st_i, st_j) \right] \tag{1}$$

f2 : balance maximization i.e. the location must allow us to maximize the balance between inflows and outflows of a station

$$f_2 = \max_{s \in \Omega} \left[\sum_{st_i \in s} \frac{f_r(st_i)}{f_T(st_i)} \right] \tag{2}$$

f3 : minimization of flow standard deviation i.e. the location must allow us to get an uniform flow along the day

$$f_3 = \min_{s \in \Omega} \left[\sum_{st_i \in s} \sqrt{\frac{1}{|T|} \sum_t (f(st_i, t) - \bar{f}(st_i))^2} \right] \tag{3}$$

With,

Ω **:** set of feasible solutions
s **:** solution element of Ω corresponding to a network of n charging stations
st_i **:** charging station i from the solution s
T **:** set of time periods of the day
t **:** one time period (for instance 15 minutes)
$f(st_i, st_j)$ **:** number of people moving from st_i to st_j on all time periods
$f(st_i, st_j, t)$ **:** number of people moving from st_i to st_j on time period t
$f(st_i, t)$ **:** number of people moving from/to st_i on time period t
$\bar{f}(st_i)$ **:** average number of people moving from/to st_i on all time periods
$f_r(st_i) = \sum_t \min \left[\sum_{st_j \in s \setminus \{st_i\}} f(st_i, st_j, t), \sum_{st_j \in s \setminus \{st_i\}} f(st_j, st_i, t) \right]$ is the balanced part of the in/out flow throughout the day
$f_T(st_i) = \sum_t \max \left[\sum_{st_j \in s \setminus \{st_i\}} f(st_i, st_j, t), \sum_{st_j \in s \setminus \{st_i\}} f(st_j, st_i, t) \right]$ is the total flow going through st_i station

4 Performance analysis

In multiobjective optimization the comparison of different algorithms is quite difficult. Indeed for two approximations of the Pareto front one can be better for a criteria but worst for another one. Choosing a comparative indicator would be a good way to distinguish these sets. Here we have considered the additive ϵ-indicator [14]. The unary additive ϵ-indicator gives the minimum factor by which a set A has to be translated to dominate the reference set R. As we do not know the optimal reference set of the problem we composed an approximated R with the best solutions obtained with PLS and FLS-MO on many runs.

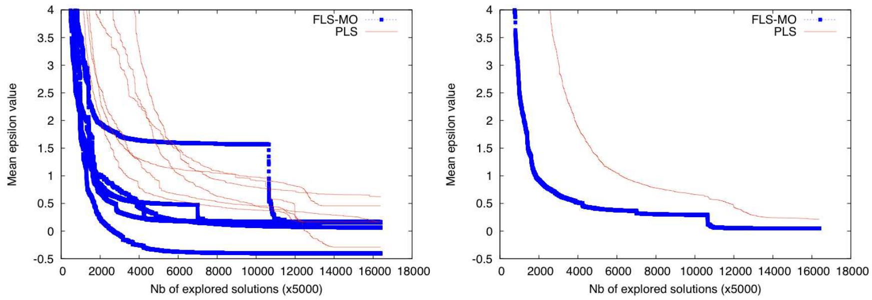

Fig. 1. ϵ-indicator evolution for PLS and FLS-MO algorithms

Figure 1 shows the comparison on 6 runs between PLS and FLS-MO. It reflects the evolution in time of ϵ-indicator. The left side shows 6 runs for each method and the right side shows their mean value on 6 runs. The results given by FLS-MO seems to be very promising. Figure 1 shows that FLS-MO converges twice faster than PLS and provides a better average evaluation.

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