A Memetic Algorithm for Multiobjective Problems

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ABSTRACT

In this article, we present a method combining a genetic approach with a local search for multiobjective problems. The performance of the proposed 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, the proposed model aims to improve: the solutions quality and the set diversity.

Categories and Subject Descriptors

G.1.6 [**NUMERICAL ANALYSIS**]: Optimization;
G.2.1 [**DISCRETE MATHEMATICS**]: Combinatorics—*Combinatorial algorithms*;
I.6.3 [**SIMULATION AND MODELING**]: Applications

Keywords

Memetic algorithm; Multiobjective optimization; Transportation services; Carsharing; Decision making

1. MEMETIC ALGORITHM FOR MULTI-OBJECTIVE PROBLEMS

The proposed algorithm is based on an hybridization of two main approaches: a Genetic Algorithm (GA) and a local search. It is a population-based algorithm which maintains an archive for collecting all non-dominated solutions reached by the algorithm. The aim is to build the Pareto set, composed of all best compromises between the different objectives [1].

The GA used in the hybridization is NSGA-II[2] proposed by Deb et al. The mutation is replaced by a local search in a selected direction. The initial population is build randomly, with n random solutions. The result is an approximation of the Pareto set. The proposed approach combines two qualities: a good intensification based on the local search and a good diversification thanks to the crossover.

For crossover and local search a direction $\omega = (\omega_1, ..., \omega_k)$ is randomly chosen with k the number of objective functions, $\omega_i \geq 0$ and $\sum_{i=1}^{k} \omega_i = 1$.

The vector direction allows to transform temporarily the MOP to a single-objective problem. Each solution has a unique fitness value f which is the weighted sum of objectives values f_i: $f = \sum_{i=1}^{k} \omega_i * f_i$

Crossover may be seen as a diversification operator. In our algorithm we propose to control the diversification with an elitist mechanism. We suppose here that each variable of an individual is associated to contribution to every objective functions. The crossover will select from each parent the best variable value according to the selected direction.

Local Search instead of the mutation is First Improvement Hill Climbing (FIHC) in which the first neighbor with a better quality is chosen (partial neighborhood exploration). Local search is a pair (Ω, V) where Ω is a set of feasible solutions (search space) and V a neighborhood structure $V : \Omega \rightarrow 2^{\Omega}$ that assigns to every $s \in \Omega$ a set of neighbors $V(s)$. Local search is applied until being in a local optimum s^* such that $\forall s \in V(s^*), f(s) \leq f(s^*)$ for a maximization problem.

Algorithm 1 Local Search: FIHC

Require: s the child coming from crossover operator
$f_s \leftarrow \sum_{i=1}^{k} \omega_i * f_i(s)$
repeat
  $s' \leftarrow$ selectNeighbor(s) {select randomly the first neighbor of s such that $f'_s > f_s$}
  if $s' \neq \varnothing$ **then**
    $s \leftarrow s'$
    $f_s \leftarrow \sum_{i=1}^{k} \omega_i * f_i(s)$
    addNotDominated(s) {add s in the archive if not dominated and remove all dominated solutions}
  end if
until s is a local optimum (i.e. $s' = \varnothing$)

2. STUDY CASE: PROBLEM AND DATA

In our study we consider a One Way Carsharing system. To deploy the service, we need to locate n stations where the people take and return the cars. Solving approaches based on exact methods already exist such as [3] but they consider simplified problem. We have applied the proposed memetic algorithm to approximate the Pareto set of this problem.

A mobility model that we have developed before is used to build the people mobility between each cell during the day. All the flows are set in a 3D matrix $F = (f_{i,j,t})$ where $f_{i,j,t}$ represents the number of people moving from the cell i to cell j at time period t. For our experimentation nearly 400 cells are considered. That gives 160,000 origin/destination couples. Considering time slots of 1/4 hour (96 per day), the flow matrix used contains more than 15,000,000 records describing how people are moving during the day.

GECCO'13 Companion, July 6–10, 2013, Amsterdam, The Netherlands.
ACM 978-1-4503-1964-5/13/07.

Stations are located by the algorithm by optimizing three objectives:

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

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

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

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

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

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

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

$f_r(st_i)$ **:** the balanced part of the in/out flow throughout the day

$f_T(st_i)$ **:** the total flow going through st_i station

3. RESULTS ANALISYS

For analyzing the results we performed 20 runs of the memetic algorithm, and we compare the results to a reference set obtained with PLS [4]. Figure 1, presents the projection of the non-dominated solutions for a typical run. Each color/shape presents the solutions for our memetic algorithm and the local search PLS.

The first important result we can see is that the memetic approach produces solutions in zones of the criteria space which are never explored by PLS.

For a more precise analyze of the results we will use indicators: the additive ϵ-indicator [5], the contribution indicator [6]and the number of solutions found.

The additive ϵ-indicator gives the minimum factor ϵ by which a set A has to be translated to dominate the set B.

$$I_{\epsilon+}(A,B) = \min_{\epsilon\in\mathbb{R}}\{\forall x\in B, \exists x'\in A : x' \preceq_{\epsilon+} x\} \quad (4)$$

The contribution indicator computes the proportion of solutions from a set A in $ND(A\cup B)$, where ND represents the non dominated solutions.

$$I_C(A,B) = \frac{\frac{|A\cap B|}{2} + |W_A| + |N_A|}{|ND(A\cup B)|} \quad (5)$$

An $I_{\epsilon+}$ value near to 0 or being negative shows a very good result. The bigger I_C value is, the better the set is.

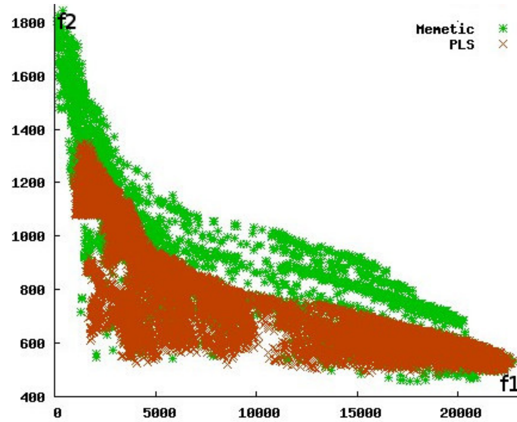

Figure 1: Projection on f1 and f2

	Memetic			PLS		
	min	**max**	**mean**	**min**	**max**	**mean**
NbSol	4515	4915	4766	8249	12969	9094
$\epsilon+$	5.135	2.921	3.719	76.621	17.232	66.050
contr	0.104	0.117	0.109	0.202	0.300	0.226

The results presented in this table give information on the fitnesses evaluation and the three indicators. For each we indicate the best value on the 20 runs, the worst of the max values, and the mean.

A significant result is that our memetic approach can't find as many solutions as PLS. But the found solutions are better spread in the criteria space.

4. REFERENCES

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