A Population-Based Method for the Bi-Objective Obnoxious p-Median Problem

Méziane Aïder[1] Aida Ilham Azzi[1] Mhand Hifi[2]

[1] LaROMaD, Fac. Maths, USTHB, BP 32 El Alia 16111, Bab Ezzouar, Alger, Algérie
`m-aider@usthb.dz, azziilham@hotmail.com`

[2] EPROAD EA 4669, UPJV, 7 rue du Moulin Neuf, 80000 Amiens, France
`hifi@u-picardie.fr`

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1 Introduction

Location problems have been widely studied in the literature, especially when tackling combinatorial optimization problems. In this work, the bi-objective obnoxious p-median (Bi-OpM) problem is studied, that is one of the variants encountered in highly sensitive area related to locations of hazardous facilities, like nuclear or chemical power plant waste storage facilities and noisy or polluting services [2]. An instance of Bi-OpM is characterized by a set I of clients, a set J of facilities J. The goal of the problem is to determine a subset of p locations optimizing two antagonistes objective functions: (i) to maximize the sum of the minimum distance between each customer and its nearest open facility dc_{ij} and, (ii) to maximize the dispersion between facilities $df_{j_1 j_2}$, where $j_1, j_2 \in S, S \subset J, j_1 < j_2$. Facilities belonging to S denote the open facilities, while those contained in $J \backslash S$ represent the closed or non-open facilities. The formal description of the bi-objective optimization may be stated as follows (cf., Colmenar *et al.* [2]):

$$\text{Bi-OpM} \begin{cases} \max f_1 = \displaystyle\sum_{i \in I} \min_{j \in S} \left\{ dc_{ij} : j \in S \right\} \\ \max f_2 = \displaystyle\sum_{j_1 \in S} \min_{j_2 \in S} \left\{ df_{j_1 j_2} : j_2 \in S; j_1 < j_2 \right\} \\ \text{s.t.} \\ S \subseteq J, \text{ and } |S| = p. \end{cases}$$

Because Bi-OpM is NP-hard, several approximate methods have been proposed to solve it [2]. Among these methods, we can cite Colmenar *et al.*'s [1] algorithm that is based upon a special randomized adaptive search tailored for the mono-objective version of the problem. For the bi-objective version of the problem, Colmenar *at al.* [2] designed a memetic algorithm to approximately solve it and, Sánchez-Oro *et al.* [3] tackled that version by using a parallel variable neighborhood search.

2 Drop and rebuild operator-based method

The problem is solved by using a two-phase procedure. The first phase attempts to provide the first (approximate) Pareto front, where a first greedy operator is called to optimize the aggregation of the two objective functions so that at least p best (efficient) solutions are stored (or completed when applying the following steps). Then, the aforementioned set is updated using an enhancing greedy procedure, which is based upon a special criterion.

The second phase is based on the drop and rebuild operator (we denoted it as an exchange between open and closed facilities), which is used to maintain a high degree of diversity of the population at hand. Each current solution is subjected to an enhancement, according to the first or second objective function, where only the non-dominated solution is returned for completing the best approximate set until no improvement is observed.

3 Preliminary results

In our preliminary experimental study, the performance of the Drop and Rebuild-based method (noted DR) was evaluated on some literature instances recently used as a benchmark for Bi-OpM.

	AOLS [2]	DBLS [2]	NSGA-II [2]	SPEA2 [2]	D and R
pmed17.p25	0.99043	0.98996	0.98833	0.98988	1.00000
pmed20.p50	0.85241	0.85427	0.80438	0.83813	1.00000
pmed22.p62	0.93020	0.93484	0.80217	0.89052	1.00000
pmed28.p75	0.93704	0.93500	0.77186	0.86092	1.00000
pmed33.p87	0.84300	0.84049	0.66233	0.74401	1.00000
pmed36.p100	0.87208	0.87477	0.66184	0.74051	1.00000
pmed39.p112	0.92524	0.92740	0.65038	0.75824	1.00000
pmed40.p225	0.80416	0.81018	0.58189	0.63038	1.00000

TAB. 1: Variation of the normalized Hypervolume value for the five tested methods, AOLS, DBLS, NSGA-II, SPEA2 and DR, on some instances of the literature.

TAB. 1 reports the normalized hypervolume achieved by the different methods on eight different instances.For each instance, the normalized hypervolume was computed as follows: the hypervolume of the algorithm divided by the maximum value reached by the five methods.

According to these preliminary results, one can observe that DR is very competitive.

4 Conclusion

In this study, we described the drop and rebuild strategy applied to the obnoxious p-median bi-objective problem. In a preliminary study, the proposed method was evaluated and compared to the best methods available in the literature on some benchmark instances. Consequently, a set with a larger hypervolume is likely to present a better set of trade-offs than sets with a lower hypervolume. From this, encouraging results have been obtained. Of course, our method will also be compared to other methods such as the one proposed by Sánchez-Oro em et al. [3] and many others.

References

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