Ranking-based Discrete Optimization Algorithm for Asymmetric Competitive Facility Location

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ABSTRACT

We address a discrete competitive facility location problem for an entering firm with a binary customers choice rule and an asymmetric objective function. A heuristic optimization algorithm which is based on ranking of candidate locations and specially adopted for the discrete facility location problems is designed. The proposed algorithm is experimentally investigated by solving different instances of the facility location problem with an asymmetric objective function.

KEYWORDS

Asymmetric Facility Location, Binary Choice Rule, Combinatorial Optimization, Random Search

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1 INTRODUCTION

A competitive facility location problems are important for firms which provide goods or services to customers in a certain geographical area and compete for the market share with other firms. There are various facility location models and strategies to solve them, which differ by their ingredients, such as a facility attraction function, customers behavior rules, decision variables, a search space, objective function(s), etc. [2, 5]).

A lot of facility location problems use a symmetric objective function, which value remains equal independent on permutations of values of variables. However, modeling a real-world application usually requires asymmetric objective function, where the position of a facility in the solution is crucial.

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2 FACILITY LOCATION PROBLEM

In this research we consider the competitive facility location problem for an entering firm, which wants to locate s new facilities with the given qualities in a geographical region where competing facilities already present. A solution to the problem consist of an s-vector where its i-th component indicates where to locate a new facility with a given quality. Since locations for the new facilities are associated with their qualities, exchange of them leads to a different solution thus making the problem asymmetric.

Customers are considered to be aggregated to geographic demand points which location and demand are known and fixed. The customers follow the binary customers behavior model in which all customer form a single demand point patronizes the most attractive facility. It may occur that there are more than one facility with maximum attraction owned by the entering firm or the competitors. If tied facilities are distributed between the entering firm and the competitor, then the entering firm captures a fixed proportion of customer's demand.

3 RANKING-BASED ALGORITHM

The Ranking-based Discrete Optimization Algorithm (RDOA) starts with an initial solution, which is stored in a pool P of the best solutions found so far and is used to generate a new solution. If P contains more than one solution, then X is randomly sampled with the sampling probability proportional to its objective function. The new solution $X^{(n)} = \{x_1^{(n)}, x_2^{(n)}, \dots, x_s^{(n)}\}$ is generated by:

$$x_i^{(n)} = \begin{cases} l \in L \setminus (X \cup X^{(n)}), & \text{if } \xi_i < 1/s, \\ x_i, & \text{otherwise,} \end{cases} \tag{1}$$

where ξ_i is a random number uniformly generated over the interval $[0, 1]$, $i = 1, 2, \dots, s$, and L is the set of all candidate locations.

A location $l_j \in L$ is selected as $x_i \in X^{(n)}$ with probability

$$\pi_{ij}^{(r)} = \frac{r_{ij}}{\sum_{k=1}^{|L|} r_{ik}}, \tag{2}$$

where r_{ij} is a rank of l_j to represent i-th new facility. Analogously, sampling probability of l_j to represent i-th new facility can be evaluated by:

$$\pi_{ij}^{(rd)} = \frac{r_{ij}}{d(l_j, x_i) \sum_{k=1}^{|L|} \frac{r_{ik}}{d(l_k, x_i)}}, \tag{3}$$

where $d(l_j, x_i)$ is a geographical distance between candidate location $l_j \in L$ and a candidate location $x_i \in X$ which is being changed.

Lets denote by $R_i = (r_{i1}, r_{i2}, \dots, r_{ij}, \dots)$ the ranks of all candidate locations from L being as a place for i-th new facility. Then all ranks can be described by the matrix R of s rows and $|L|$ columns. Initial values of R are equal to 1 and are dynamically adjusted with respect to success and failures when generating a new candidate solution. If the newly generated solution $X^{(n)}$ is better than the worst solution $X^{(w)} \in P$, then $X^{(n)}$ is included in P and ranks of candidate locations which form the new solution are updated by:

$$r_{ij} = \begin{cases} r_{ij} + 1, & \text{if } l_j = X_i^{(n)}, \\ r_{ij}, & \text{otherwise.} \end{cases} \tag{4}$$

The ranks of all candidate locations which form a solution in P which is improved by $X^{(n)}$, but do not belong to $X^{(n)}$ are reduced by $r_{ij} = r_{ij} - k$, where $k = |\{X \subset P : x_i = l_j \wedge M(X) < M(X^{(n)})\}|$, $i = 1, 2, \ldots, s$, and $j = 1, 2, \ldots, |L|$. If $X^{(n)}$ do not improve the worst solution $X^{(w)} \in P$, then the ranks of all candidate locations are updated as follows:

$$r_{ij} = \begin{cases} r_{ij} - 1, & \text{if } l_j = x_i \wedge l_j \neq x_i^{(w)} \\ r_{ij}, & \text{otherwise.} \end{cases} \tag{5}$$

If the size of P exceeds its size limit n_P, then the worst solution is removed from P. Reducing rank values can make a rank equal to zero or negative value, e.g. $r_{ij} = -k$, where $k \geq 0$. Then all ranks in R_i are increased by $k + 1$.

After processing the newly generated solution the algorithm continues to the next iteration, where another solution X is sampled from P to generate a new solution $X^{(n)}$. The procedure continues till stopping criterion is satisfied, which is based on the number of function evaluations. The maximal pool size n_P is given as an algorithm parameter and is further reduced by removing a half worst solutions after every 20% of function evaluations.

The algorithm which uses only the ranks to evaluate sampling probabilities for candidate locations is denoted by RDOA and the algorithm, which includes geographical distance – by RDOA-D.

4 EXPERIMENTAL INVESTIGATION

The experiment was focused on selecting optimal locations for 3 new facilities from a set of 500 and 1000 candidate locations considering randomly generated qualities for the new facilities. Both versions of RDOA, 5000 function evaluations were devoted to evaluate the optimal solution with the maximal pool size $n_P = 64$. Due to stochastic nature of the algorithms, 100 runs were performed for each experiment and average results were recorded.

The performance of the proposed algorithm was compared with the performance of Genetic Algorithm (GA) [3], which was successfully applied to CFLPs in [1, 4]. The population size in GA was set to 64, the crossover and mutation rates were 0.8 and $1/s$.

The results are presented in Figure 1, where the left image presents results of the instance with 500 candidate location and the right one – with 1000 candidate locations. The horizontal axis of a graph stands for the number of function evaluations and the vertical one – for the percent of market share captured by the new facilities.

One can see from the figures, RDOA without geographical distance outperforms GA in both cases. Significant difference appears in early stage of the algorithm, what means that RDOA is able to

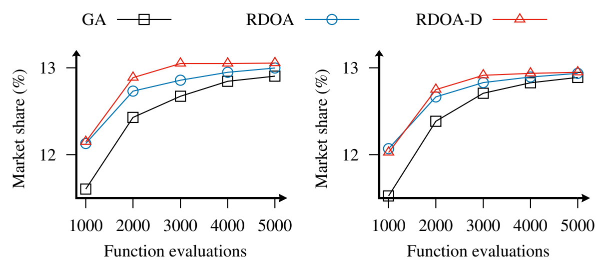

Figure 1: Results of the performance of the algorithms.

find much more better solution in the beginning of the procedure, e.g. after 1000 function evaluations. The advantage of inclusion of geographical distance in calculation of sampling probabilities for candidate locations (RDOA-D) is notable in the later stage of the algorithm; it is specially notable in the instance with 500 candidate locations, where the best performance is achieved after 3000 function evaluations. Inclusion of the geographical distance is a kind of a local search and is more useful when updating a good candidate solution. This could be the reason for lower performance at the beginning of the algorithm. It is worth to note that, the average of objective value found after 5000 functions evaluations using RDOA-D is close to the optimal objective value, and probability to determine the optimal solution is close to 1.

5 CONCLUSIONS

The ranking-based heuristic algorithm for asymmetric discrete competitive facility location was proposed and investigated. The algorithm is based on the ranking of candidate locations for the new facilities and includes geographical distance when sampling a new candidate location. The results of the experimental investigation demonstrate that the proposed heuristic is able to effectively approximate the optimal solution of the actual problem.

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