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Solution of Discrete Competitive Facility Location Problem for Firm Expansion

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Abstract. A new heuristic algorithm for solution of bi-objective discrete competitive facility location problems is developed and experimentally investigated by solving different instances of a facility location problem for firm expansion. The proposed algorithm is based on ranking of candidate locations for the new facilities, where rank values are dynamically adjusted with respect to behaviour of the algorithm. Results of the experimental investigation show that the proposed algorithm is suitable for the latter facility location problems and provides good results in sense of accuracy of the approximation of the true Pareto front.

Key words: facility location, multi-objective optimization, heuristic algorithms.

1. Introduction

Facility location deals with determination of the optimal locations for the facilities providing goods or services in a given geographical area. There are a lot of factors which must be taken into account when considering a certain location for establishing a facility, such as customers behaviour when choosing to buy a service; the market environment, which includes other firms already in the market (the competitors); the restrictions for the new locations, which includes minimum distance from the living areas in order to avoid negative to the citizens possibly caused by the new facility, etc. However, the most important factor, from the point of view of the solution of the problem, is the objective (or a set of them) of the location of the new facilities, which covers various aspects such as maximization of the market share of the firm establishing the new facilities, minimization of the cost for establishment, maintenance of or communication with the new facility as well as minimization of the undesirable effect caused by the new facility. These criteria can be considered separately or several criteria can be considered at once, thus solving a *multi-objective facility location problem*.

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There are a lot of models of facility location problems proposed in the literature, e.g. in Friesz (1998), Plastria (2001), ReVelle *et al.* (2008), which differ in various properties including the above ones. According to the market environment, the problem of facility location taking into account the competition for the market with other firms already carrying out a commercial activity in the region of interest, are known as *Competitive Facility Location Problems* (CFLPs). Depending on the location space, the CFLP can be formulated as *continuous*, in which new facilities can be located everywhere in the given area (or with some restrictions), and a *discrete* one, where locations for the new facilities are chosen from a predefined set of candidate location.

We will consider that one of the firms already in the market is planning to expand its market share by establishing a set of new facilities taking into account the competition with other firms in the market and the following two objectives: (1) maximization of the market share of the new facilities and (2) minimization of the undesirable effect in the sense of lost market share to the preexisting facilities of the same firm (cannibalization effect). In Pelegrin *et al.* (2012, 2014), this effect is integrated in the objective function as a cost to be paid by the expanding firm to the cannibalized facilities, and the bi-objective model is reduced to a single discrete optimization problem. In this paper, we will study this model as a bi-objective discrete competitive facility location problem for firm expansion, and it will be solved by using multi-objective optimization techniques. For the simplicity of writing, we will call the latter CFLP by Competitive Facility Location Problem for Firm Expansion, denoted by CFLP/FE hereinafter.

The remainder of the paper is organized as follows: Sections 2 and 3 describe the relevant CFLP/FE and principles of multi-objective optimization used to tackle the problem, respectively; Section 4 describes our proposed algorithm for CFLP/FE, and Section 5 is devoted for description of the experimental investigation of the proposed algorithm and discussion of the results obtained; finally, conclusions are formulated in Section 6.

2. Competitive Facility Location Problem for Firm Expansion

Consider a geographical region where customers are spatially spitted into a set I of demand points. Two firms A and B have sets F_A and F_B of n_A and n_B preexisting facilities, respectively, already providing a service or goods to the customers in I and competing with each other for the market share. The customers at a single demand point behave depending on the predefined rules – the model of customers behaviour. In this research we will focus on the binary model for customers behaviour, where all customers from a single demand points patronize the most attractive facility (Hakimi, 1995; Suárez-Vega *et al.*, 2004, 2007), assuming that the attractiveness of the facility is based on a distance between a demand point and the facility – smaller distance leads to more attractive facility.

Firm A is interested to expand its market share by establishing a set X of d new facilities. On the one hand, firm A is interested to increase the total market share by attracting customers from the competitors, but, on the other hand, the expanding firm does not want to negatively affect the market share of its own preexisting facilities by redirecting their customers to the newly established facilities. It is especially important, when the expanding firm has different owners, as it occurs in franchise systems. Thus, firm A faces a bi-objective optimization problem to determine optimal locations for d new facilities with respect to (1) maximization of the market share of the new facilities and (2) minimization of the loss of market share of its own preexisting facilities (also known as the effect of cannibalism).

Locations for the new facilities can be selected from the discrete set

$$L = \{l_1, l_2, \dots, l_m\} \tag{1}$$

of candidate locations. Thus, the solutions of the problem is a subset

$$X = \{x_1, x_2, \dots, x_d\} \tag{2}$$

of L, where d is the number of the facilities expected to locate. Depending on whether a single or multiple facilities can be located in a single candidate location, the subset X is of repetitive or non-repetitive elements.

Let's denote by $M(X)$ the market share obtained by the set X of new facilities, and by $C(X)$ the cannibalized market share. Such an undesirable effect is called *cannibalism*, which was studied for the first time in franchise systems in Ghosh and Craig (1991). Then the CFLP/FE mathematically can be described as

$$\begin{cases} \max\limits_{X \in D} M(X), \\ \min\limits_{X \in D} C(X), \end{cases} \tag{3}$$

where the search space D describes all possible subsets $X \subset L$ of the size d.

3. Multi-Objective Optimization

Due to conflicting objectives, usually it is impossible to find a single solution of the problem (3), which would be the best by both objectives. Moreover, the comparison of two solutions by a single objective is meaningless as the best solution by one objective can be worse by another one. In multi-objective optimization, two solutions X_1 and X_2 can be compared to each other by the dominance relation; it is said that solution X_1 dominates X_2 if

(1) solution X_1 is not worse than X_2 by all objectives and
(2) solution X_1 is strictly better than X_2 by at least one objective.

The relation is denoted by $X_1 \succ X_2$, and X_1 is called dominator of X_2. The solution X, which has no dominators in a set $D' \subset D$ is called non-dominated in the set D', and the solution which has no dominators in the whole search area D is called Pareto-optimal.

The set of Pareto-optimal solutions is called the Pareto set, and the corresponding set of objective values of Pareto-optimal solutions is called the Pareto front.

Determination of the true Pareto set usually is computationally- and time-consuming task. Therefore, approximation methods for an approximate determination of Pareto-optimal solutions are popular for the solution of practical problems. A well-known class of such methods suitable for discrete multi-objective optimization is evolutionary algorithms, e.g. NSGA-II (Deb *et al.*, 2002), SPEA2 (Zitzler *et al.*, 2001), VEGA (Schaffer, 1985), etc. Evolutionary algorithms have a wide area of applicability as they do not require specific knowledge on the problem being solved – the only requirement is to have a possibility to evaluate objective values for any feasible solution.

Various evolutionary algorithms have been applied to solve various multi-objective optimization problems in facility location. For example, Redondo *et al.* (2012) proposed a general multi-objective optimization heuristic algorithm, suitable to continuous multi-objective optimization problems; Huapu and Jifeng (2009) utilized SPEA to solve a multi-objective bi-level programming model to optimize the location problem of distribution centres, where the upper level consists of two objectives: minimization of cost of construction and distance between distribution centre and customers, whereas the lower level minimizes the transportation cost; Villegas *et al.* (2006) utilized NSGA-II to solve a bi-objective facility location problem by minimizing operational cost of Colombian Coffee supply network and maximizing the demand; Liao and Hsieh (2009) used NSGA-II to optimize the location for distribution centres with respect to two objectives: maximization of customers service and minimization of the total cost; Medaglia *et al.* (2009) utilized hybrid NSGA-II and mixed-integer programming approach to solve bi-objective obnoxious facility location problem related to the hospital waste management network.

The following section describes our proposed algorithm for solution of discrete multi-objective facility location problem, which is applied for CFLP/FE, described above.

4. Multi-Objective Random Search with Ranking

The proposed algorithm, called Multi-Objective Random Search with Ranking (MO-RSR) is based on generation of new solutions by applying modification to the non-dominated solutions found so far by the same algorithm or found by another algorithm and given to MO-RSR as input parameters. The modification is performed by changing the elements (the locations) of a non-dominated solution to another ones, randomly selected from the set of candidate locations L. It is assumed that each candidate location $l_i \in L$ has its own probability π_i to be selected, which is proportional to the rank r_i of l_i.

For the simplicity we will denote by $r(L)$ the (set of) ranks of all candidate locations in set L, where L can be changed to any entity indicating a set or a subset of locations. The notation $r(L) = 1$ refers to the setting of all ranks in $r(L)$ to one or other given value instead of one. Similarly, the notations $r(L) + 1$ and $r(L) - 1$ refer to increment and reduction of all ranks $r(L)$ by one or other given value instead of one.

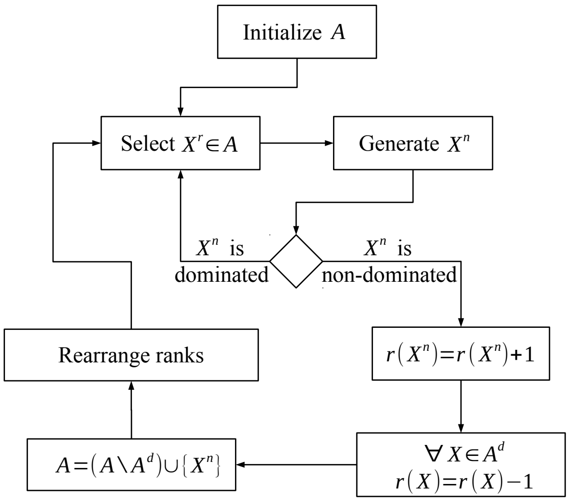

Fig. 1. Scheme of MO-RSR algorithm.

The MO-RSR algorithm, illustrated by scheme in Fig. 1, begins with an initial set A of non-dominated solutions. A new solution X^n is generated by applying changes to the elements of reference solution X^r randomly selected from A. Each element of X^r is changed with predefined probability $1/d$ to the element l, randomly selected from the set indicating all possible candidate locations without those already forming X^r and X^n. The element $x_i^n \in X^n$ can be mathematically expressed by

$$x_i^n = \begin{cases} l \in L', & \text{if } \xi_i < \frac{1}{d}; \\ x_i^n, & \text{otherwise,} \end{cases} \tag{4}$$

where l is selected at random from $L' = L \setminus (X^r \cup X^n)$, $\xi_i \in [0, 1]$ is an uniform random number, and $i = 1, 2, \ldots, d$. Thus, a probabilistic selection of elements to be a changed leads to a change of averagely one element per generation. See Lančinskas *et al.* (2013) for detailed description and advantages of the latter approach.

Each candidate location $l_i \in L$ has an appropriate probability π_i to be selected, which is evaluated in proportion to the rank r_i of the corresponding candidate facility.

At the beginning of the algorithm, all candidate locations have unity rank values: $r(L) = 1$. Next, the rank of a particular candidate location is dynamically adjusted depending on the successes and failures when including the location to form a new solution. In particular, if the newly generated solution X^n is non-dominated in A, then the ranks of all candidate locations forming X^n are increased by one:

$$r(X^n) = r(X^n) + 1. \tag{5}$$

Thus, the candidate locations in X^n are assumed to be more promising as they form a non-dominated solution, and will have larger probability to be included when forming a new solution in the future.

Additionally, if X^n dominates a solution from A, then the ranks of candidate locations which form a dominated solution, but do not form its dominator X^n are reduced by one. Let's denote by $A^d \subset A$ a set of solutions from A, which are dominated by X^n. Then for all solutions $X \in A^d$

$$r\big(X \setminus X^n\big) = r\big(X \setminus X^n\big) - 1. \tag{6}$$

Thus, the latter candidate locations are assumed to be less promising and will have lower probability to be selected when generating a new solution in the future.

In order to avoid negative and non-proportional large ranks, they are arranged so that the minimum worst rank value would be equal to one. The latter arrangement is performed by the following expression:

$$r(L) = \begin{cases} r(L) - \min r(L) + 1, & \text{if } \min r(L) > 1; \\ r(L) + \min r(L) + 1, & \text{if } \min r(L) < 1; \\ r(L), & \text{otherwise.} \end{cases} \tag{7}$$

Once a non-dominated solution X^n is generated, the population A is updated by including X^n and removing all the solutions dominated by X^n. The updated population can be mathematically described by

$$A = \big(A \setminus A^d\big) \cup \big\{X^n\big\}. \tag{8}$$

The ranks of candidate locations are the basis when evaluating the probability to select a particular candidate location when forming a new solution; larger rank value of a candidate location leads to a larger probability to select the latter location. The probability π_i to select the candidate location l_i is evaluated by

$$\pi_i = \frac{r_i}{\sum_{j=1}^{|L|} r_j}. \tag{9}$$

Such an iterative process of generation of new solutions and their fitness evaluation is continued until the stopping criteria, usually based on the number of function evaluations, is satisfied.

5. Experimental Investigation

The performance of the proposed MO-RSR algorithm has been experimentally investigated and compared with the performance of NSGA-II applied for the same CFLP/FE. Three instances of the problem have been solved:

- to select 5 locations for the new facilities from the set of 500 candidate locations;
- to select 5 locations for the new facilities from the set of 1000 candidate locations;
- to select 10 locations for the new facilities from the set of 1000 candidate locations.

Table 1
Indices of demand points, where preexisting facilities of firms A and B are located.

Firm	Indices of the demand points									
A	9	15	17	1	4	14	2	16	18	20
B	6	11	13	5	12	8	10	7	3	19

In the first two cases the optimization problem has 5 variables but different search space, whereas in the third instance the number of problem variable has been increased to 10.

Real data of 6090 demand points in Spain with geographical coordinates and populations has been used, assuming that firms A and B have 10 preexisting facilities per each, located at random in 20 largest demand points. See Table 1 for the indices of demand points, where preexisting facilities of firms A and B are located.

A predefined number of 10 000 function evaluations has been devoted for each approximation of the Pareto front. Due to stochastic nature of the algorithms under investigation, each experiment has been run for 100 times, using different, randomly generated, initial solutions (a set of them for NSGA-II).

The NSGA-II has been implemented and adapted for CFLP/FE using the same strategies for crossover and mutations as in Genetic Algorithm, specially adopted for CFLP for an entering firm in Lančinskas *et al.* (2015). After a series of experiments with different parameters of NSGA-II, the following set of parameters has been chosen for further investigation:

- population size: 100;
- probability for crossover: 0.6;
- probability for mutation: $1/d$.

5.1. *Metric of Performance*

The measurement of performance of the proposed algorithm is based on Hyper-Volume (HV) metric (Zhou *et al.*, 2006). The HV evaluates quality of the obtained approximation of the Pareto set by measuring the area made by the members of the approximation and the given reference point.

For the evaluation of results, obtained by the algorithm under investigation, we use a modified version of HV metric – the Rational HV (RHV), which additionally includes the results obtained by Pure Random Search (PRS) assuming them as the worst case results. RHV, concept which is illustrated in Fig. 2, measures how an algorithm under investigation performs better than PRS in the sense of HV, and it is evaluated by

$$RHV_A = \frac{HV_A - HV_{PRS}}{HV_{PRS}}, \tag{10}$$

where HV_A and HV_{PRS} is the HV values of Pareto front approximations, obtained by the algorithm under investigation and PRS, respectively.

For the reasons of uniformity, approximations of the Pareto front are scaled to the unity hyper-cube $[0, 1]^m$ (with respect to extreme points in the true Pareto front), and the

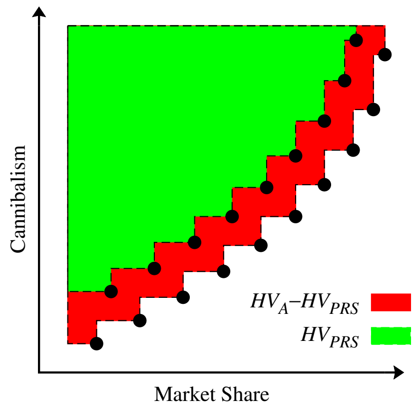

Fig. 2. Illustration of the relative hyper-volume metric.

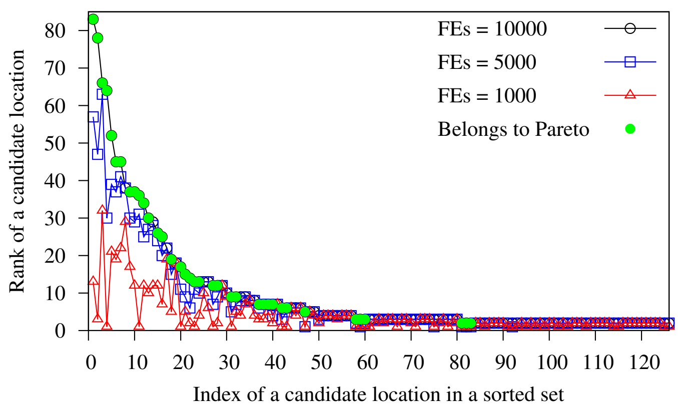

Fig. 3. Ranks of the candidate locations after 1000, 5000, and 10 000 function evaluations with candidate locations from Pareto set indicated.

corresponding vertex of the box is then chosen as the reference point for evaluation of HV; here m is the number of optimization problem objectives. Since we deal with 2 objectives one of which is subject to maximization while another one to minimization, the obtained approximations are scaled to the square $[0, 1]^2$ and the point $(0, 1)$ is considered as the reference point.

5.2. *Results and Discussion*

As it was mentioned in Section 4, all rank values of the candidate location are equal to the one at the beginning of the algorithm. Later on, the rank values are updated according to the results obtained. Figure 3 illustrates the change of the rank values according to the number of function evaluations performed. The horizontal axis stands for the indices of elements in the set formed of candidate locations with the rank values larger than 1 after 10 000 function evaluations (126 at all), which is sorted by the rank values in descending

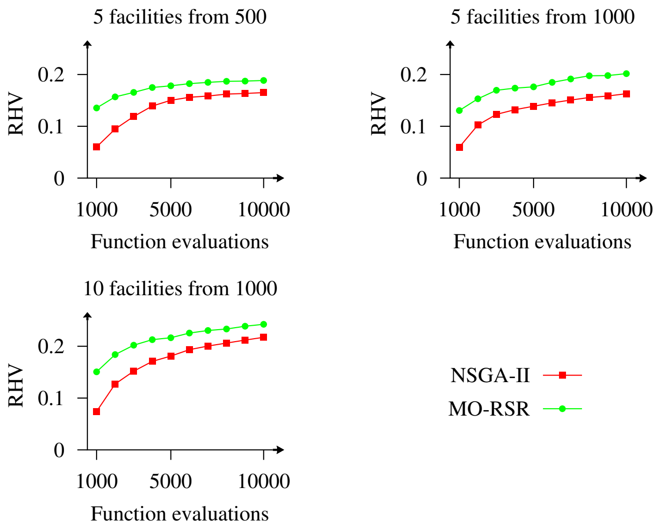

Fig. 4. Average results obtained by MO-RSR and NSGA-II for CFL/FE when selecting locations for 5 and 10 facilities from the set 500 and 1000 candidate locations.

order. The circle-marked graph illustrates the final rank values of the candidate locations, where filled circles indicate optimal candidate locations forming a non-dominated solution in the obtained approximation of the Pareto set (optimal candidate locations hereinafter).

It can be seen from figure that all optimal candidate locations have a rank value larger than 1, and only 6 of them have a rank value lower than 5. The triangle-marked graph shows that noticeably higher ranks of the optimal candidate locations appear even in the early stage of the algorithm – after 1000 function evaluations. However, some of the optimal candidate locations still have zero ranks, but after 5000 function evaluations their ranks obtain values corresponding to their quality.

There also exists a correlation between the rank value of an optimal candidate location and its appearance in the Pareto set approximation and in the true Pareto set – the candidate locations with larger rank values in the final stage of the algorithm statistically form more non-dominated solutions in the same Pareto set.

The average values of the RHV metric with respect to the number of function evaluations performed are illustrated in Fig. 4. Different plots correspond to different instances of the problem being solved by two algorithms: NSGA-II and the proposed MO-RSR. The results show significant advantage of MO-RSR against the well known NSGA-II independent on the instance of the problem investigated as well as on the number of function evaluations.

The results presented in Figs. 3 and 4 show that the ranking of candidate locations leads to the extraction of the most promising candidate locations, which is useful when determining the probability to select a certain candidate location to form a new solution in MO-RSR (whereas all candidate locations have the same probability to be selected in NSGA-II) herewith leading to a better accuracy of approximation of the Pareto front within the same number of function evaluations.

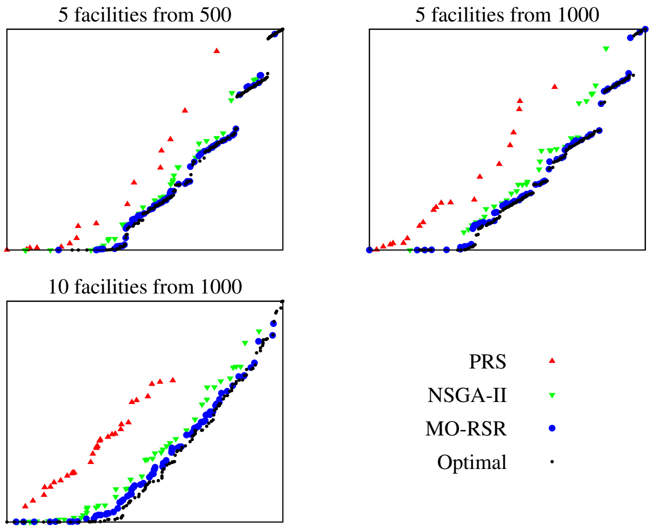

Fig. 5. Selected approximations of the true Pareto fronts, obtained by different algorithms, in the context of the true Pareto front.

The selected approximations of the Pareto front, obtained by PRS, NSGA-II, and MO-RSR are illustrated in Fig. 5 in the context of the true Pareto front. The illustrated results show that most of the Pareto-optimal solutions are determined by MO-RSR for the simplest case of the relevant CFLP/FE. The similar conclusion can be also made for the second instance – selection of locations for 5 new facilities from the set of 1000 candidate locations. However, only a few of Pareto-optimal solutions are determined by MO-RSR for the problem to select locations for 10 new facilities from the set of 1000 candidate locations, but, as it was in previous cases, there is notable advantage of MO-RSR against NSGA-II in the sense of accuracy of the approximation.

6. Conclusions

The new heuristic algorithm MO-RSR for the solution of bi-objective discrete competitive facility location problems has been developed and experimentally investigated by solving different instances of the facility location problem for firm expansion. The results of the experimental investigation of the proposed algorithm showed significant advantage of MO-RSR against the well known NSGA-II independent on the instance of the problem investigated as well as on the number of function evaluations. Analysis of the selected approximations of the Pareto front showed that MO-RSR is able to determine almost all Pareto-optimal solutions for the problem of selection of locations for 5 new facilities from the set of 500 candidate locations. Although it is complicated for MO-RSR to find locations for 10 new facilities having a set of 1000 candidate locations, the algorithm still shows notably better performance in the sense of accuracy of the approximation, than NSGA-II, which is considered as a good algorithm for such kind of optimization problems.

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Konkuruojančių objektų vietos parinkimo diskrečiųjų uždavinių rinkoje besiplečiančioms įmonėms sprendimas

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Straipsnyje siūlomas naujas euristinis algoritmas dviejų kriterijų konkuruojančių objektų vietų parinkimo uždaviniams spręsti. Algoritmo, grįsto potencialių vietų naujiems objektams rangavimu, efektyvumas vertinamas sprendžiant įvairius konkuruojančių objektų vietų parinkimo uždavinius, aktualius besiplečiančiai rinkoje jau esančiai įmonei. Eksperimentinio tyrimo rezultatai parodė, kad siūlomas optimizavimo algoritmas efektyviai sprendžia minėtus uždavinius, vertinant pagal Pareto fronto aproksimacijos tikslumą.