3rd International Scientific Convention UCLV 2021
“Science, Technology & Society”

“Transferencia de Conocimiento en Tecnologías de la Información”

Demand allocation approaches for the capacitated maximal covering location problem
(Enfoques de asignación de demanda para el problema de localización de máxima cobertura capacitado)

Luis Suárez, Cynthia Porras, Alejandro Rosete

[a] *Universidad Tecnológica de La Habana ”José Antonio Echeverría”(CUJAE)*
[b] *Universidad Tecnológica de La Habana ”José Antonio Echeverría”(CUJAE)*
[c] *Universidad Tecnológica de La Habana ”José Antonio Echeverría”(CUJAE)*

Resumen

The maximal covering location problem seeks to locate a limited number of facilities to maximize the covered demand. Commonly facilities are modeled with unlimited capacity, but this is not realistic, and in many situations, facilities have workload limits. A limited capacity means that it is also necessary to find the best allocation of customers to the facilities. This paper presents six demand node allocation procedures for the capacitated maximal coverage location problem. Performed experiments show that the descending allocation of the demand nodes to the closest facility nodes with available capacity obtains the best results, achieving a 3 % improvement over the worst allocation procedure resulted from the experiments.

Palabras clave: Demand allocation; Capacitated; Location; Coverage

1. Introduction

Among the fundamental goals of logistics is customer satisfaction in the best conditions of service, cost and quality Meiduté-Kavaliauskiené et al. (2014). Many situations within logistics can be modeled as a

Email address: `lsuarezgo@ceis.cujae.edu.cu` (Luis Suárez).

.

location problem, where it is necessary to geographically manage the allocation of resources to satisfy the customers. The maximal covering location problem (MCLP) aims to locate a set of facilities to maximize the covered demand of the customers. The MCLP was first introduced in 1974 Church and ReVelle (1974). The objective of this problem is to find the best combination of the p facilities to maximize the covered demand Church and ReVelle (1974). The MCLP has been applied in economy and society scenarios, such as: police patrol planing Fajardo et al. (2017), location of Wi-Fi antennas Lee and Murray (2010), location of bank branches Allahi et al. (2015), distribution of drones for medical care Pulver et al. (2016), location of mining bases Xue et al. (2016), location of facilities for entertainment shows North and Miller (2017), among others.

In the previous cases, facilities are modeled with unlimited capacity, but this restriction is often necessary to be considered in real-world scenarios Xu et al. (2020). The first variant of MCLP with capacitated facilities (CMCLP) was proposed in 1983 Chung et al. (1983). The idea is to limit the workload of the facilities. By introducing capacity restrictions to the facilities, a new problem arises: how to allocate demand nodes to facilities to maximize the satisfied demand or used capacity Church and Murray (2018). One of the challenges in the application of the CMCLP is the study of the implications of allocation strategies Xu et al. (2020). In addition, the CMCLP is an NP-Hard problem and large instances cannot be solved in a reasonable time by exact methods Xu et al. (2020). Heuristic and metaheuristic methods have proven to obtain high-quality solutions in a reasonable time, as stated in Pirkul and Schilling (1991); Shariff et al. (2012); Murray et al. (2019). Several proposals have been made to solve the CMCLP by means of heuristics and metaheuristics, for example: Greedy Adding Church and ReVelle (1974), Tabu Search Gendreau et al. (1997); Arostegui Jr et al. (2006), Genetic Algorithm Arostegui Jr et al. (2006), Variable Neighbourhood Search Davari et al. (2013), among others.

Metaheuristics have been widely used to solve the CMCLP and its variants. Therefore, is necessary to study the implications of allocation strategies in the amount of demand covered. For this proposal, six heuristic procedures for the allocation of demand nodes to facilities are proposed to solve the CMCLP using metaheuristic algorithms. Since the use of an allocation procedure has an impact on the amount of demand covered and the capacity used, an analysis of obtained solutions for each allocation procedure is performed, with the objective of determining the allocation that obtains the highest value of demand served and capacity usage.

2. Methodology

2.1. Capacitated maximal covering location problem (CMCLP)

The objective of CMCLP is to maximize the total demand served by locating p facilities with capacity constraints. The parameters and variables that define the CMCLP are the following Xu et al. (2020):

- i, I: the index and set of demand nodes.
- j, J: the index and set of facility sites.
- a_i: population or demand of the node i.
- c_j: capacity of the facility j.

- d_{ij}: the shortest distance (or time) from demand node i to the facility j.
- p: number of facilities to be located.
- S: coverage distance. It is the minimum distance (or time) required between a demand node and facility in order to be considered to be covered.
- N_i: $\{j|d_{ij} \leq S\}$ set of potential facilities that can cover the demand generated in i.
- X_j: $\{0, 1\}$ a binary variable which equals 1 if the facility is placed at node j, 0 otherwise.
- Y_{ij}: $\{0, 1\}$ a binary variable which equals 1 if the demand node i is served by the facility j, 0 otherwise.

The objective function is:

$$Maximize : Z = \sum_{i \in I} \sum_{j \in N_i} a_i Y_{ij} \tag{1}$$

Subject to:

$$\sum_{j \in J} X_j = p \tag{2}$$

$$\sum_{j \in N_i} Y_{ij} \leq 1, \forall i \in I \tag{3}$$

$$\sum_{i \in I} a_i Y_{ij} \leq c_j X_j, \forall j \in J \tag{4}$$

The objective function 1 seeks to maximize the total demand served by the facilities. Constraint 2 indicates that the number of opened facilities must be p. Constraint 3 ensures each demand node is allocated to only one facility of the N_i set. Finally, constraint 4 ensures that the total demand served by a facility should not be more than its capacity c_j.

Imposing capacity restrictions to facilities in location problems bring along five fundamental issues Xu et al. (2020). The first is associated with defining an appropriate capacity for the facility. The second problem is that capacity might not be an exact limit. Therefore, some degree of relaxation of the constraint may be required. The third problem is the rejection of clients due to capacity limitations. This problem leads to the allocation of clients to a further away facility or another that does not improve the system utility. Another issue is that the capacity restriction imposed may not reflect the actual workload of facilities. Finally, the addition of capacity constraints complicates the computational processing of model solutions, making it impossible to find exact solutions in a reasonable time for some cases. Due to capacity limitations, facilities can not serve all demand nodes within the service area. Therefore, it is necessary to determine which demand nodes to allocate. One approach to manage this issue is to take into account the quality of service based on travel time Pirkul and Schilling (1991). This approach aims to allocate demands to the closest facility. Another proposal maximizes the covered demand and minimizes the average distance between the demand nodes and the facilities Haghani (1996). An alternative can be to minimize the cost of transportation from the facilities to the distribution centers and maximize the covered demand Jabalameli et al. (2010). Finally, an additional approach consists of a dynamic model where the objective is to maximize the covered demand, ensuring that each demand node is served by the closest facility, penalizing assignments with excess travel time Delmelle et al. (2014). The first two proposals treat the closest assignment as an objective function and the third impose a restriction for demand allocation to the closest facility.

In the context of capacitated location problems, there are three main perspectives to determine the allocation of demand nodes to facilities: user optimal, system optimal, and equal fraction Church and Murray (2018). User optimal perspective states that the system does not decide which facility serves a client's demand. In this case, the client chooses the facility that is more suitable for his convenience. When demand node allocation is not dependent on the system, many capacitated models assume that the closest facility to the demand node provides the service. In Gerrard and Church (1996) is presented an analysis on this type of assignment. In addition, the authors proposed an equitable allocation of demand nodes to equally nearby facilities for the CMCLP.

The closest assignment states that a demand node should be assigned to the nearest facility with the capacity to serve it and within its coverage. Some examples are retail stores, libraries, post offices, among others Church and Murray (2018). In these examples, demand nodes do not need to have a priority to be served. However, other contexts like emergency services may need to define a priority among the demand nodes to be served and consider situations where the system does not control which facility serves a demand.

The system convenience perspective is applied when the system has control over which demand node will be served by each facility, taking into account some characteristics of the system or an assignment that maximizes its utility Church and Murray (2018). This perspective has been the default approach when formulating capacitated models Church and Murray (2018). There are many cases in which the system is responsible for the allocation of demand nodes. In police patrol, it is convenient for the system to decide which police officer serves an incident. It would also be reasonable to apply the closest assignment approach since the response time is a key element in this context. In this example, priorities for demand nodes served must be defined, since not all incidents have the same importance.

Another example of system convenience could be the location of distribution centers. Unlike the above examples, in this situation demand nodes could be treated without any priority. Therefore, the goal would be to maximize the number of demand nodes served and, as a default approach, to allocate demand nodes to the closest facility. An alternative to allocate customers to the closest facility is to define a threshold distance that the customer would be willing to travel in to access a certain service Díaz et al. (2017). In this case, is necessary to define an ordered list of preferences containing the facilities within service distance by each client.

When it is impossible to determine the behavior of the demand nodes, an equal fraction perspective can be applied. This perspective is applied when there is not enough knowledge about the system to predict how it will behave. The idea is to have a set of facilities that can provide service to a demand node and since there is no knowledge about the preferences of the node, the probability that these facilities will serve it is the same Church and Murray (2018). An example of the equal fraction perspective can be found in Balakrishnan and Storbeck (1991), a model for the location of retail stores with capacity restrictions. The proposed model states that a demand node can be covered by more than one facility, distributing the portion of demand covered among facilities within service distance. Another example of the equal fraction perspective can be the location of cellular towers. In this context, there is no control over which tower will serve a user and there are no priorities among the users since the goal is to serve the maximal amount of cell phones.

Most of the found proposals take into account the selection of the facility that serves a demand node, but none of them focus on the fact that due to capacity limitations it may be required to define demand nodes assignment priority when occupying facilities capacity. However, there is a geographical component that establishes a relationship between the assignments and the different facilities.

2.2. Procedures for demand allocation

In this section six demand nodes allocation procedures to obtain total demand served Z are proposed. These are divided into two groups by the selection process of the facility that serves each demand. The first group selects facilities randomly (RF), where each facility has the same probability to be selected. The second group is aimed to allocate each demand node to the closest facility (NF) with the capacity to serve it.
Finally, three types of priorities to select the demand node to allocate are defined: maximum demand (MaxD), minimum demand (MinD), and random demand (RD). These priorities show how the capacity of the facilities is occupied. The MaxD allocation prioritizes the demand nodes with the highest demand values a_i, therefore, the capacity of each facility is occupied in a descendant order. In the case of MinD allocation, demand nodes are prioritized in ascendant order. As for RD allocation, demand value is not taken into account, and demand nodes are randomly assigned to the selected facility. Finally, by combining facility selection with demand allocation priority, six demand allocation procedures are obtained (RFMaxD, RFMinD, RFRD, NFMaxD, NFMinD, and NFRD).
The Algorithms 1 and 2 describe the procedures for demand nodes allocation according to the type of facility selection (RF and NF). Both procedures receive as a parameter the demand allocation type (I_{order}) that establishes the type of priority used.

2.2.1. Demand allocation to a random facility (RF)

This procedure allows the allocation of demand nodes to a located facility with the capacity to serve them and $d_{ij} \leq S$. Each located facility where $d_{ij} \leq S$ has the same probability to serve the demand node i. Demand nodes are served in an order defined by the parameter I_{order}=$\{$MaxD, MinD, RD$\}$. It is worth noticing that given the random component of this procedure, it is not deterministic. Algorithm 1 describes the demand allocation procedure. The procedure *sortDemandNodes*, sorts the demand nodes taking into account the established order by I_{order}. The procedure *sortFacilitiesByRandomOrder* sorts the facilities in random order.

2.2.2. Demand allocation to the nearest facility (NF)

This allocation procedure takes into account the perspectives of closest assignment and system convenience described above. Each demand node i is allocated to the nearest located facility j with the capacity to serve it and $d_{ij} \leq S$. Algorithm 2 describes the demand allocation procedure. Procedure *sortDemandNodes* sorts the demand nodes using the order specified by I_{order}= $\{$MinD, MaxD, RD$\}$. Procedure *sortFacilitiesByDistance* obtains the facilities J sorted by d_{ij} to the demand node i.

2.3. Computational experiments

In this section, computational experiments performed in several scenarios are presented. First, the test instances are described. Next, a solution method for the CMCLP is presented. Finally, obtained solutions

Algorithm 1 Allocation to a random facility (RF)

```
procedure RF(I_order)
    I' = sortDemandNodes(I, I_order)
    C[] = ∅
    J' = sortFacilitiesByRandomOrder(J)
    j = 0
    repeat
        if X_j = 1 then
            i = 0
            repeat
                if j ∈ N_i & C[j] + a_i ≤ c_j then
                    Y_ij = 1
                    C[j] += a_i
                i++
            until i = |I'| or Y_{i-1 j} = 0
        j++
    until j = |J'|
```

Algorithm 2 Allocation to the nearest facilities (NF)

```
procedure NF(I_order)
    I' = sortDemandNodes(I, I_order)
    C[] = ∅
    i = 0
    repeat
        J' = sortFacilitiesByDistance(J, i)
        j = 0
        repeat
            if X_j = 1 & j ∈ N_i & C[j] + a_i ≤ c_j then
                Y_ij = 1
                C[j] += a_i
            j++
        until j = |J'| or Y_{i j-1} = 1
        i++
    until i = |I'|
```

are statistically analyzed to determine the allocation procedures that accomplish the best results in terms of served demand and used capacity.

2.3.1. Instances description

Two groups (A and B) of 2000 and 3000 demand nodes (with 150 and 250 possible facility locations, respectively) are defined. In the instances of group A, demand nodes and facilities coordinates are generated randomly over a $30x30$ grid, following a uniform distribution, similar to the approach presented in Bag-

herinejad and Shoeib (2018). In the instances of group B, the coordinates of both facilities and demand nodes are a subset of the points of fi10639 dataset, from the Travelling Salesman Problem (TSP) instance repository Cook (2019).
In both cases, the coverage radius S is calculated as $S = 0{,}1 * max(d_{ij})$. Demand values a_i are uniformly selected randomly in the interval $[0,100]$. Capacity values c_j are computed as $c_j \approx \alpha * (\sum a_i)/(0{,}5 * |J|)$ Xu et al. (2020), where α adjust the value of c_j and takes values of $\alpha = \{0{,}4, 0{,}5, 0{,}6\}$ respectively . For each instance five values of p are defined, which correspond to the $30, 40, 50, 60$ and 70% of $|J|$. As a result, with 2 groups (A and B) $*5$ values of $p * 3$ values of α, 30 sets of test instances are obtained. These instances are available at OneDrive cloud service for replication.

2.3.2. *Solving the CMCLP test instances using Iterated Local Search*

Proposed allocation procedures are unable to obtain the solution of the CMCLP by themself, they need facilities to be previously located to perform the allocation of demand nodes. In this sense, to obtain a solution of the defined instances and to evaluate the allocation procedures proposed, the Iterated Local Search (ILS) metaheuristic is used Talbi (2009). Considering this, the CMCLP is modeled and solved as an optimization problem using the framework BiCIAM Fajardo (2015), which provides an implementation of the ILS metaheuristics and the required elements to define the subordinated heuristics. In our study, the six allocation procedures are used to determine the objective function value determined by the amount of demand covered achieved by the demand allocation obtained.

Representation of the solutions

To apply metaheuristic algorithms, a representation of the solution of CMCLP must be defined. The solutions are coded in two parts. The first part corresponds to a binary list of size $|J|$ which represents the model variable X_j, taking values of 1 if facility j is opened, and 0 otherwise. The second part keeps track of demand nodes allocation. A binary matrix with size $|I|x|J|$ is defined, which corresponds to the variable Y_{ij}. In this case, for each pair (i, j), the value 1 indicates that the demand node i is allocated to facility j, and 0 otherwise. Figure 1 represents the codification of a solution with $|I| = 3$, $|J| = 4$ and $p = 2$.

X_1	X_2	X_3	X_4
1	0	1	0

	Y_{i1}	Y_{i2}	Y_{i3}	Y_{i4}
Y_{1j}	1	0	0	0
Y_{2j}	0	0	1	0
Y_{3j}	1	0	0	0

Figura 1. Solution codification example. (Own elaboration)

Initial solution and perturbation procedures

To obtain the initial solution, a greedy-add approach is used Church and ReVelle (1974). This consists in opening facilities in descending order, considering the amount of demand that each facility contributes independently. Therefore, this approach obtains optimal solution when locating $p = 1$ facilities, although for $p > 1$ optimal solutions are not guaranteed Church and ReVelle (1974).
To explore the solution space a set of four mutation operators is used. These consist in performing exchanges between opened and closed facilities. The first is named 2-swap Tabrizi et al. (2011). This operator selects two facilities randomly, one opened, and one closed. Then, the values of these facilities are exchanged in the solution, resulting in opening the previously closed facility and closing the one opened.
The second operator is called 2-swap with roulette Davari et al. (2013), where the facility selection is ma-

de using a roulette constructed by the probability of a facility to cover or not the demand nodes. Finally, the facilities that cover the greatest amount of demand will have a high probability of being opened and the facility with the lowest demand coverage will have a high probability of being closed. The last two operators are the k-swaps and k-swaps with roulette Fazel Zarandi et al. (2013), which follow the same principles as the above operators, but they exchange *k* facilities at the same time.

3. Results and Discussion

To compare the performance of approximated algorithms, non-parametric statistical tests can be applied to justify the conclusions obtained from the analysis Derrac et al. (2011). Therefore, to determine the allocation procedure that obtains the best objective function value (amount of total demand served), the Friedman non-parametric test Friedman (1937) is applied. This test allows determining if there is a significant difference in the performance of all allocation procedures. In case the significant difference is determined by the Friedman test, the Holm post-hoc procedure Holm (1979) is performed to determine which algorithms had significant differences concerning the algorithm with the best performance. These tests were performed using the software KEEL Isaac et al. (2017), with a significance value $\alpha = 0{,}05$. The local search algorithm was executed 30 times with 10000 iterations for each instance under the six allocation procedures. This solutions were obtained using a laptop with an Intel Core i5-5200U CPU and 8GB of DDR3-RAM. For each instance, average demand served and used capacity are analyzed. Average demand served corresponds to average objective function value, determined y the equation $\sum_{i\in I}\sum_{j\in N_i} a_i Y_{ij}$. As for average used capacity, the fraction from the total capacity of facilities used is determined by the equation $(\frac{\sum_{i\in I}\sum_{j\in J} a_i Y_{ij}}{\sum_{j\in J} c_j * x_j})$. As a result of the experiments, the solutions of the 30 test instances of CMCLP were obtained. Table 1 shows the average of total demand served obtained from the 30 best solutions for each instance for each allocation procedure. Next to each average, is shown the associated standard deviation (σ) and the percent $[\%]$ of the average of total demand served.
The results in Table 1 show that the best average was obtained by NFMaxD and RFMaxD, and the worst allocation procedures are RFMinD and NFMinD. It can be noted that the σ was small in almost all cases, except the MinD allocations. The fact that RFMinD and NFMinD have a high standard deviation could indicate that the local search procedure did not converge to good solutions and a higher number of iterations could be required.

Cuadro 1
Av. average total demand served, (σ), [%] for each allocation procedure. Best values are in bold. (Own elaboration)

					RFMaxD	RFMinD	RFRD	NFMaxD	NFMinD	NFRD
Data	S	α	c_j	p	Av. (σ) [%]	Av. (σ) [%]	Av. (σ) [%]	Av. (σ) [%]	Av. σ [%]	Av. (σ) [%]
A	4.5	0.4	529	45	**23805** (0) [24]	23184 (27) [23]	23792 (2) [24]	**23805** (0) [24]	23405 (36) [24]	23788 (2) [24]
				60	**31740** (0) [32]	30771 (43) [31]	31715 (2) [32]	**31740** (0) [32]	31059 (40) [31]	31703 (3) [32]
				75	39674 (1) [40]	38320 (33) [39]	39632 (2) [40]	**39675** (0) [40]	38659 (81) [39]	39609 (5) [40]
				90	47607 (1) [48]	45833 (35) [46]	47545 (5) [48]	**47610** (0) [48]	46205 (84) [47]	47499 (7) [48]
				105	55540 (1) [56]	53277 (63) [54]	55448 (4) [56]	**55545** (0) [56]	53624 (90) [54]	55368 (11) [56]
		0.5	689	45	**29745** (0) [30]	29062 (26) [29]	29732 (2) [30]	**29745** (0) [30]	29311 (44) [30]	29727 (2) [30]
				60	**39660** (1) [40]	38594 (46) [39]	39632 (3) [40]	**39660** (0) [40]	38910 (56) [39]	39618 (4) [40]
				75	49574 (1) [50]	48063 (44) [48]	49528 (3) [50]	**49575** (0) [50]	48471 (80) [49]	49498 (7) [50]
				90	59487 (1) [60]	57497 (34) [58]	59415 (6) [60]	**59490** (0) [60]	57958 (96) [58]	59347 (9) [60]
				105	69400 (1) [70]	66839 (42) [67]	69285 (7) [70]	**69405** (0) [70]	67299 (112) [68]	69158 (16) [70]
		0.6	794	45	**35730** (0) [36]	34982 (30) [35]	35714 (2) [36]	**35730** (0) [36]	35239 (51) [35]	35708 (2) [36]
				60	**47640** (0) [48]	46487 (57) [47]	47608 (3) [48]	**47640** (0) [48]	46831 (63) [47]	47591 (5) [48]
				75	59549 (1) [60]	57907 (57) [58]	59494 (5) [60]	**59550** (0) [60]	58292 (90) [59]	59449 (6) [60]
				90	71457 (1) [72]	69260 (58) [70]	71359 (5) [72]	**71460** (0) [72]	69731 (95) [70]	71254 (13) [72]
				105	83362 (2) [84]	80501 (79) [81]	83172 (15) [84]	**83369** (1) [84]	80947 (111) [82]	82941 (21) [84]
B	1133.8	0.4	481	75	**36075** (0) [24]	34997 (37) [23]	36062 (2) [24]	**36075** (0) [24]	35293 (64) [23]	36051 (3) [24]
				100	**48100** (0) [32]	46388 (44) [31]	48071 (3) [32]	**48100** (0) [32]	46847 (83) [31]	48043 (4) [32]
				125	**60125** (0) [40]	57761 (61) [38]	60072 (3) [40]	**60125** (0) [40]	58285 (128) [39]	60015 (7) [40]
				150	**72150** (0) [48]	69010 (54) [46]	72066 (4) [48]	**72150** (0) [48]	69619 (155) [46]	71971 (8) [48]
				175	**84175** (1) [56]	80230 (75) [53]	84048 (6) [56]	**84175** (0) [56]	80774 (190) [54]	83894 (12) [56]
		0.5	601	75	**45075** (0) [30]	43875 (25) [29]	45061 (2) [70]	**45075** (0) [30[	44216 (78) [29]	45048 (3) [30]
				100	**60100** (0) [40]	58224 (47) [39]	60067 (3) [40]	**60100** (0) [40]	58649 (102) [39]	60033 (4) [40]
				125	**75125** (0) [50]	72519 (69) [48]	75067 (4) [50]	**75125** (0) [50]	73024 (130) [49]	74993 (8) [50]
				150	**90150** (0) [60]	86709 (81) [58]	90053 (5) [60]	**90150** (0) [60]	87332 (145) [58]	89919 (10) [60]
				175	**105175** (1) [70]	100867 (54) [67]	105028 (0) [70]	**105175** (0) [70]	101454 (189) [67]	104786 (18) [70]
		0.6	721	75	**54075** (0) [36]	52756 (44) [35]	54060 (2) [36]	**54075** (0) [36]	53116 (68) [35]	54043 (3) [36]
				100	**72100** (0) [48]	70067 (60) [47]	72065 (2) [48]	**72100** (0) [48]	70490 (118) [47]	72022 (5) [48]
				125	**90125** (0) [60]	87277 (75) [58]	90058 (4) [60]	**90125** (0) [60]	87843 (133) [58]	89963 (10) [60]
				150	**108150** (0) [72]	104392 (105) [69]	108031 (6) [72]	**108150** (0) [72]	104929 (185) [70]	107832 (17) [72]
				175	126174 (1) [84]	121354 (77) [81]	125967 (9) [84]	**126175** (0) [84]	121839 (252) [81]	125575 (35) [84]

Table 2 shows the rankings obtained by the Friedman test for instances A, B, and Global stage. In all cases, the $p-value$ of the test is less than the significance level α. This confirms the existence of significant differences among the algorithms. The allocation procedure with the best ranking is NFMaxD, both globally and in each group of instances A and B. The worst ranking was obtained by the procedure RFMinD, being the one with the lowest average of total demand served. Compared with NFMaxD, NFMaxD allocation achieves an improvement of 3,21 % of demand served with respect to RFMinD. It is worth noting how RFRD and NFRD have a small difference with the best allocation procedure NFMaxD in instance group B, with $\alpha = 0{,}6$ and locating $p = 175$ facilities.

Cuadro 2
Results of Friedman test for average total demand served. The best values are marked in bold. (Own elaboration)

	Friedman			Post-Hoc p-values		
Method	Global	A	B	Global	A	B
RFMaxD	1.67	1.80	1.53	0,49	0,38	0,92
RFMinD	6.00	6.00	6.00	0,00	0,00	0,00
RFRD	3.00	3.00	3.00	0,00	0,01	0,04
NFMaxD	**1.33**	**1.20**	**1.47**	*	*	*
NFMinD	5.00	5.00	5.00	0,00	0,00	0,00
NFRD	4.00	4.00	4.00	0,00	0,00	0,00
$p-value$	0.00	0.00	0.00			

"$*$": control algorithm.

Table 2 also shows the results of post-hoc procedure to determine which allocation procedures had significant differences with respect to the algorithm with the best performance. In this case, the results of the post-hoc show that NFMaxD has significant differences with respect to the other allocation procedures, except RFMaxD. As it can be noted, both allocation procedures share MaxD order type. To illustrate the distribution of the opened facilities obtained by the allocation procedures, Figure 2 shows the solutions of an instance of group B with $p = 75$ and $\alpha = 0{,}6$. The solutions show that using RFMinD and NF-MinD there is a higher number of demand nodes served with a low demand value a_i. For this reason, these allocations procedures obtain a low overall demand served. As the capacity of the facilities is used with demand nodes with low a_i, the remaining capacity cannot be used to cover demand nodes with high a_i. However, allocating demand nodes randomly (RD) obtains a certain balance in the number of demand nodes covered with low and high a_i. This way, RFRD, and NFRD allocation procedures have a higher percentage of total demand served than RFMinD and NFMinD, and still, these procedures manage to cover a higher population of demand nodes than RFMaxD and NFMaxD. For this reason, it could be said that RD procedures accomplish a certain balance between the benefits of both MaxD and MinD procedures.

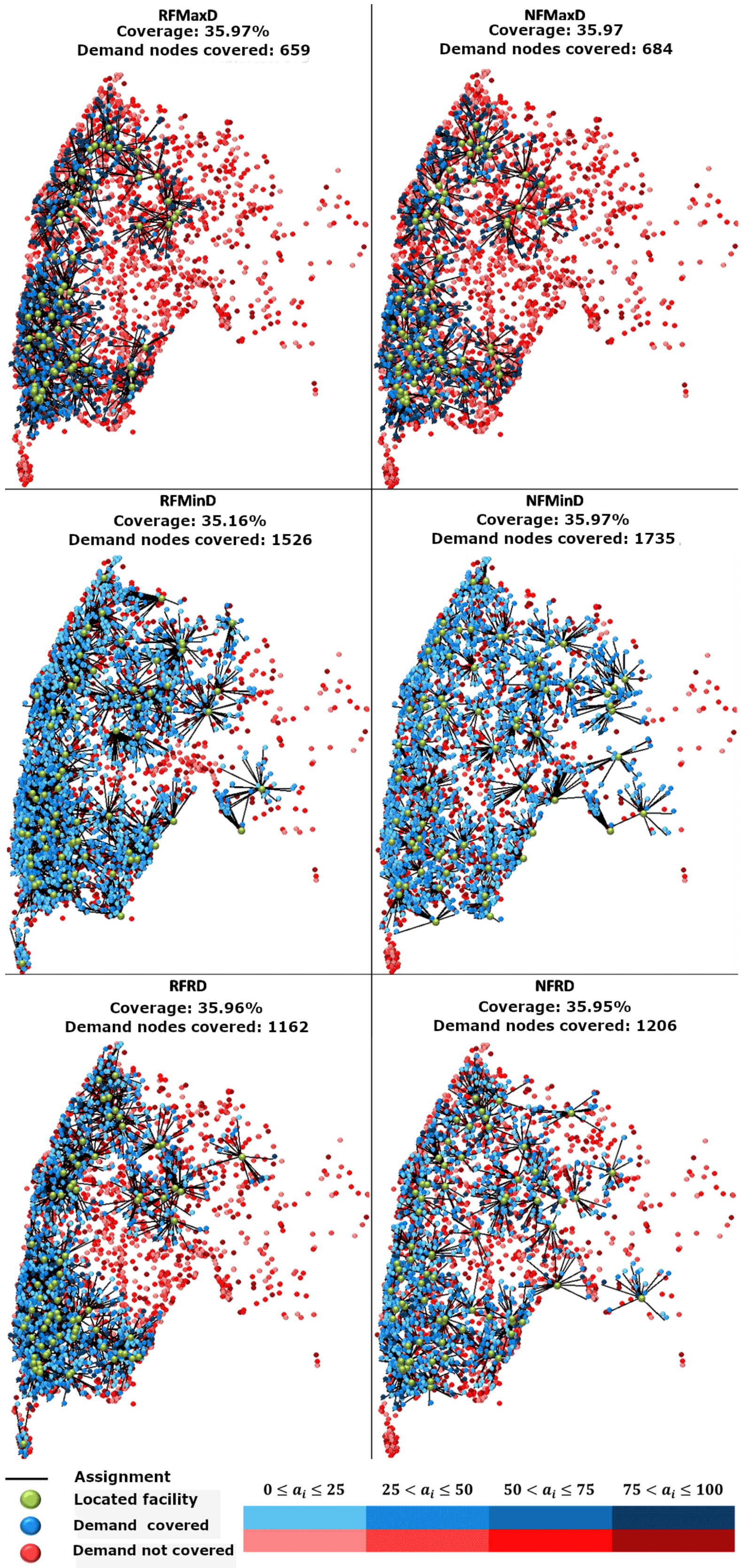

Figura 2. Representation of obtained solutions by allocation procedure. (Own elaboration)

Another aspect to note is the facilities located by RFMaxD and NFMaxD procedures, as they tend to locate facilities where there is a concentration of demand nodes with high demand value a_i. As for RFMinD and NFMinD procedures, higher dispersion of located facilities is obtained, covering almost all the area. This behavior can be useful in situations where the number of demand nodes covered is more important than the demand value a_i. In the case of RFRD and NFRD procedures, the same dispersion pattern as MinD order type can be noted. Another aspect to be noted is that NF procedures show more concentric clusters of allocated demand nodes, in some cases avoiding the assignment of demand nodes inside the service area of another facility.

Figure 3 shows the solutions obtained by RFMaxD and NFMaxD in more detail. As can be noted, the NFMaxD solution has allocations between demand nodes and facilities with a d_{ij} lower than RFMaxD, obtain an overall travel time or distance smaller than RFMaxD procedure. The NF allocations try to assign demand nodes to the nearest facility, but sometimes there is no other option than to allocate a demand node to a farther facility, due to capacity restrictions and resulting in some long assignments. Figure 3 also shows how some demand nodes inside service area (S) are not covered due to capacity limits.

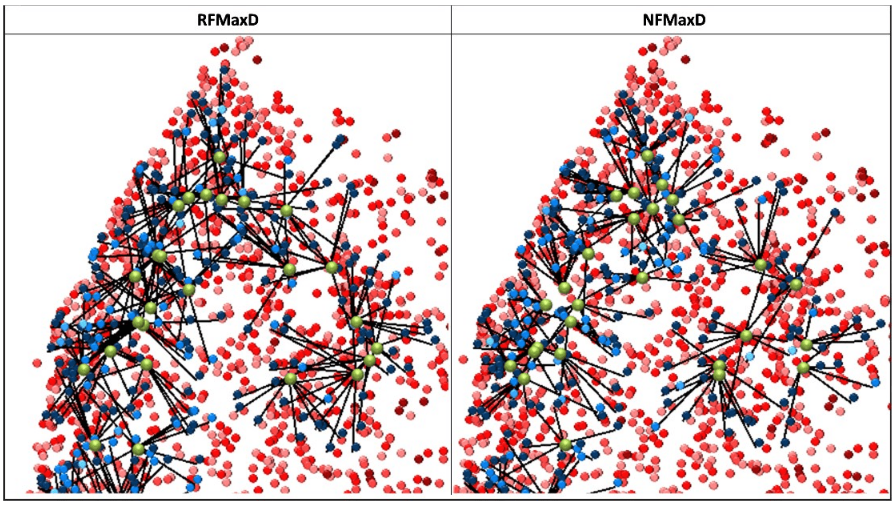

Figura 3. Fragment of solutions obtained by procedures RFMaxD y NFMaxD. (Own elaboration)

Another aspect to take into account evaluating the performance of the allocation procedures is the use of the capacity. The highest average used capacity was obtained by RFMaxD and NFMaxD, where in most cases there is 100 % of usage. The RFRD and NFRD procedures achieved usage near to 100 %. In the case of RFMinD and NFMinD procedures, both achieved the lowest capacity usage, with a maximum of 97 % for RFMinD and 98 % for NFMinD.

4. Conclusions

In this paper, six demand node allocation procedures for the CMCLP are proposed. These procedures come from the need to better use the limited capacity of facilities to maximize the total demand served. After performing statistical tests, the NFMaxD allocation procedure obtained the best performance, improving

the solution obtained by the worst procedure, RFMinD, by 3 %. The NF procedures allow a reduction of travel distance between facilities and their assigned demand nodes.
Using RFMinD and NFMinD allocation procedures, located facilities are more dispersed across the analyzed region in comparison with RFMaxD and NFMaxD. As opposed to this behavior, NFMaxD and RFMaxD tend to locate the facilities in areas where the overall demand value is high. In terms of capacity usage, NFMaxD and RFMaxD allocation procedures manage to occupy most of facilities capacity, exploiting to the maximum facilities workload capacity.

5. Bibliographic references

Referencias

Allahi, S., Mobin, M., Vafadarnikjoo, A., Salmon, C., 2015. An integrated ahp-gis-mclp method to locate bank branches, in: Proceedings of the 2015 Industrial and Systems Engineering Research Conference, Norcross, Georgia. pp. 1104–1113.

Arostegui Jr, M.A., Kadipasaoglu, S.N., Khumawala, B.M., 2006. An empirical comparison of tabu search, simulated annealing, and genetic algorithms for facilities location problems. International Journal of Production Economics 103, 742–754.

Bagherinejad, J., Shoeib, M., 2018. Dynamic capacitated maximal covering location problem by considering dynamic capacity. International Journal of Industrial Engineering Computations 9, 249–264.

Balakrishnan, P.V., Storbeck, J.E., 1991. Mcthresh: Modeling maximum coverage with threshold constraints. Environment and Planning B: Planning and Design 18, 459–472. URL: https://doi.org/10.1068/b180459, doi:doi: 10.1068/b180459, arXiv:https://doi.org/10.1068/b180459.

Chung, C., Schilling, D., Carbone, R., 1983. The capacitated maximal covering problem: A heuristic, in: Proceedings of Fourteenth Annual Pittsburgh Conference on Modeling and Simulation, pp. 1423–1428.

Church, R., ReVelle, C., 1974. The maximal covering location problem. Papers of the Regional Science Association 32, 101–118. doi:doi: 10.1111/j.1435-5597.1974.tb00902.x.

Church, R.L., Murray, A., 2018. Location Covering Models: History, Applications and Advancements. Advances in Spatial Science. 1ra ed., Springer International Publishing AG.

Cook, W., 2019. The Traveling Salesman Problem (TSP). Technical Report. Department of Combinatorics and Optimization, University of Waterloo, Available: http://www.math.uwaterloo.ca/tsp/index.html.

Davari, S., Zarandi, M.H.F., Turksen, I.B., 2013. A greedy variable neighborhood search heuristic for the maximal covering location problem with fuzzy coverage radii. Knowledge-Based Systems 41, 68–76.

Díaz, J.A., Luna, D.E., Camacho-Vallejo, J.F., Casas-Ramírez, M.S., 2017. Grasp and hybrid grasp-tabu heuristics to solve a maximal covering location problem with customer preference ordering. Expert Systems with Applications 82, 67–76. URL: https://www.sciencedirect.com/science/article/pii/S0957417417302361, doi:doi: https://doi.org/10.1016/j.eswa.2017.04.002.

Delmelle, E.M., Thill, J.C., Peeters, D., Thomas, I., 2014. A multi-period capacitated school location problem with modular equipment and closest assignment considerations. Journal of Geographical Systems 16, 263–286. doi:doi: 10.1007/s10109-013-0195-2.

Derrac, J., García, S., Molina, D., Herrera, F., 2011. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. Swarn and Evolutionary Computation 1, 3–18. doi:doi: 10.1016/j.swevo.2011.02.002.

Fajardo, J., 2015. Soft Computing en Problemas de Optimización Dinámicos. Ph.d. thesis. Granada University.

Fajardo, J., Porras, C., Sanchez, L., Estrada, D.E., 2017. Software tool for model and solve the maximum coverage location problem, a case study: Locations police officers. Revista de Investigación Operacional (RIO) 38, 141–149.

Fazel Zarandi, M.H., Davari, S., Haddad Sisakht, S.A., 2013. The large-scale dynamic maximal covering location problem. Mathematical and Computer Modelling 57, 710–719. doi:doi: 10.1016/j.mcm.2012.07.028.

Friedman, M., 1937. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32, 675–701. doi:doi: 10.2307/3001968.

Gendreau, M., Laporte, G., Semet, F., 1997. Solving an ambulance location model by tabu search. Location science 5, 75–88.

Gerrard, R.A., Church, R.L., 1996. Closest assignment constraints and location models: Properties and structure. Location Science 4, 251–270. URL: `https://www.sciencedirect.com/science/article/pii/S0966834997000016`, doi:doi: https://doi.org/10.1016/S0966-8349(97)00001-6.

Haghani, A., 1996. Capacitated maximum covering location models: Formulations and solution procedures. Journal of Advanced Transportation 30, 101–136. doi:doi: 10.1002/atr.5670300308.

Holm, S., 1979. A simple sequentially rejective multiple test procedure. Scandinavian Journal of Statistics 6, 65–70. URL: `http://www.jstor.org/stable/4615733`.

Isaac, T., Sergio, G., Jose, M.M., Salvador, G., Jesús, A.F., Julián, L., Alberto, F., Maria José del, J., Luciano, S., Francisco, H., 2017. Keel 3.0: An open source software for multi-stage analysis in data mining. International Journal of Computational Intelligence Systems 10, 1238–1249. doi:doi: 10.2991/ijcis.10.1.82.

Jabalameli, M.S., Bankian Tabrizi, B., Moshref Javadi, M., 2010. Capacitated facility location problem with variable coverage radius in distribution system. IUST 21, 231–237. URL: `http://ijiepr.iust.ac.ir/article-1-240-en.html`.

Lee, G., Murray, A.T., 2010. Maximal covering with network survivability requirements in wireless mesh networks. Computers, Environment and Urban Systems 34, 49–57. doi:doi: 10.1016/j.compenvurbsys.2009.05.004.

Meidutė-Kavaliauskienė, I., Aranskis, A., Litvinenko, M., 2014. Consumer satisfaction with the quality of logistics services. Procedia - Social and Behavioral Sciences 110, 330–340. URL: `https://www.sciencedirect.com/science/article/pii/S1877042813055171`.

Murray, A.T., Xu, J., Wang, Z., Church, R.L., 2019. Commercial gis location analytics: capabilities and performance. International Journal of Geographical Information Science 33, 1106–1130.

North, J., Miller, F.L., 2017. Facility location using gis enriched demographic and lifestyle data for a traveling entertainment troupe in bavaria, germany. Decision Support Systems 99, 30–36. doi:doi: 10.1016/j.dss.2017.05.007.

Pirkul, H., Schilling, D.A., 1991. The maximal covering location problem with capacities on total workload. Management Science 37, 233–248. doi:doi: 10.5555/2913379.2913387.

Pulver, A., Wei, R., Mann, C., 2016. Locating aed enabled medical drones to enhance cardiac arrest response times. Prehospital Emergency Care 20, 378–389. doi:doi: 10.3109/10903127.2015.1115932.

Shariff, S.R., Moin, N.H., Omar, M., 2012. Location allocation modeling for healthcare facility planning in malaysia. Computers & Industrial Engineering 62, 1000–1010. URL:

https://www.sciencedirect.com/science/article/pii/S0360835211003998, doi:doi: https://doi.org/10.1016/j.cie.2011.12.026.

Tabrizi, B.B., Jabalameli, M.S., Moshref Javadi, M., 2011. A simulated annealing method to solve a generalized maximal covering location problem. International Journal of Industrial Engineering Computations 2, 439–448. doi:doi: 10.5267/j.ijiec.2011.01.003.

Talbi, E.G., 2009. Metaheuristics: From design to implementation. John Wiley & Sons, Inc., New Jersey. doi:doi: 10.1002/9780470496916.

Xu, J., Murray, A., Wang, Z., Church, R., 2020. Challenges in applying capacitated covering models. Transactions in GIS 24, 268–290. doi:doi: 10.1111/tgis.12608.

Xue, Y., Wen, Z., Ji, X., Bressers, H.T.A., Zhang, C., 2016. Location optimization of urban mining facilities with maximal covering model in gis: A case of china. Journal of Industrial Ecology 21, 913–923. doi:doi: 10.1111/jiec.12467.