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Estudio experimental con varios enfoques de asignación de demanda en el problema de localización de máxima cobertura capacitado

An experimental study with several demand allocation approaches for the capacitated maximal covering location problem

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Resumen

El problema de localización de máxima cobertura ha sido ampliamente aplicado en contextos donde es necesaria la ubicación de instalaciones que brindan un servicio determinado. Este problema busca ubicar un número limitado de instalaciones con el objetivo de maximizar la cobertura sobre un conjunto de nodos de demanda. Usualmente las instalaciones son modeladas con capacidad ilimitada, pero este enfoque no es realista ya que en muchas situaciones estas poseen una carga de trabajo limitada. La limitación en la capacidad implica que es necesario determinar la mejor asignación de los nodos de demanda a las instalaciones. Este trabajo presenta seis criterios de asignación de demanda para el problema de localización de máxima cobertura capacitado. Se realiza un análisis experimental donde se resuelven varias instancias del problema, donde los resultados indican que la asignación en orden descendente de las demandas a la instalación más cercana con capacidad para cubrirla obtiene los mejores resultados.

Palabras clave: Asignación de demanda, capacidad, localización, cobertura

ABSTRACT

The maximal coverage location problem has been widely used in contexts where it is necessary to locate facilities to provide a service. This 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 the best results are obtained by asigning nodes in descending order of demands to the closest facility with available capaciy.

Keywords: Demand allocation, Capacitated, Location, Coverage

Introduction

Among the fundamental goals of logistics is customer satisfaction in the best conditions of service, cost and quality. Many situations within logistics can be modeled as a 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 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), 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). 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 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. One approach is to maximize the covered demand and to minimize the average distance between the demand nodes and the facilities Haghani (1996),Jabalameli et al. (2010).

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, the system decides which unit 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.

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 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.

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. 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 metaheu-

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ristic methods have proven to obtain high-quality solutions in a reasonable time, as stated in 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), Genetic Algorithm Arostegui Jr et al. (2006), Variable Neighbourhood Search Davari et al. (2013),Iterated Local Search (ILS) Pitakaso and Sindhuchao (2021), among others.

Many of the reviewed proposals to solve the CMCLP establish an allocation procedure according to the context the model is applied to, yet no analysis has been found respect to the implications of an allocation procedure to the amount of demand covered. In this article, we propose six demand allocation procedures that aim to cover the three demand allocation perspectives stated in Church and Murray (2018). Given the selected facilities to be opened, these allocation procedures determine which facility covers each demand taking into account the capacity restrictions. Our objective is to evaluate the influence of these allocation in the amount of demand covered achieved using Iterated Local Search (ILS) metaheuristic, determining which allocation procedure achieves the highest amount of demand covered.

Computational Methodology

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.

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

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 exceed its capacity c_j.

Procedures for demand allocation

In this section six demand nodes allocation procedures 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 define 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,

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NFMinD, and NFRD).

These procedures are applied after a heuristic has determined which facilities to open. Algorithm 1 describes an example of the application of these allocation procedures with ILS metaheuristics for the solution of the CMCLP. The algorithm takes as inputs the allocation_procedure to be applied, the set of demand nodes I, the set of facilities J, the amount of facilities to be open p and the amount of iterations. After a solution is constructed or mutated, the allocation procedure is applied (lines 3 and 8).

Algorithm 1 Application of allocation procedures within ILS

```
1:  procedure ILS_ALLOCATION(allocation_procedure,I,J,p,amount_iterations)
2:    S0 =generate_initial_solution(I,J,p)
3:    allocate_demands(S0,allocation_procedure,I)
4:    S_Incumbent =local_search(S0)
5:    iteration = 0
6:    repeat
7:      S' =mutate(S0)
8:      allocate_demands(S',allocation_procedure,I)
9:      S'' =local_search(S')
10:     if evaluate(S'') > evaluate(S_Incumbent) then
11:       S_Incumbent = S''
12:     iteration = iteration + 1
13:   until iteration = amount_iterations
```

The Algorithms 2 and 3 describe the procedures for demand nodes allocation according to the facility type of selection (RF and NF). The most expensive operation in these procedures is the sorting procedure applied to the demand nodes and facilities. RF procedure only sorts the demand nodes and facilities at the beginning; in the worst case the amount of demand nodes and facility locations is the same. Since demand nodes are sorted in $T(n) = nlog(n)$ and facility locations can be shuffled in $T(n) = n$, the temporal complexity of the procedure is $O(nlog(n))$. In the NF procedure, the demand nodes are sorted only once at the beginning in $T(n) = nlog(n)$; but for each demand node to allocate facilities are sorted, resulting in $T(n) = n^2log(n)$. Considering this, the complexity of NF procedure is $O(n^2log(n))$.

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Algorithm 2 Random facility allocation (RF)

procedure RF(I_{order})
  $I' = sortDemandNodes(I, I_{order})$
  $C[] = \emptyset$
  $J' = shuffleFacilities(J)$
  $j = 0$
  repeat
    if $X_j = 1$ & $j \in N_i$ **then**
      $i = 0$
      repeat
        if $C[j] + a_i \leq c_j$ & $Y_{ij} = 0$ **then**
          $Y_{ij} = 1$
          $C[j] += a_i$
        $i{+}{+}$
      until $i = |I'|$
    $j{+}{+}$
  until $j = |J'|$

Algorithm 3 Nearest facility allocation (NF)

procedure NF(I_{order})
  $I' = sortDemandNodes(I, I_{order})$
  $C[] = \emptyset$
  $i = 0$
  repeat
    $J' = sortFacilitiesByDistance(J, i)$
    $j = 0$
    repeat
      if $X_j = 1$ & $j \in N_i$ **then**
        if $C[j] + a_i \leq c_j$ & $Y_{ij} = 0$ **then**
          $Y_{ij} = 1$
          $C[j] += a_i$
      $j{+}{+}$
    until $j = |J'|$ or $Y_{ij-1} = 1$
    $i{+}{+}$
  until $i = |I'|$

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 based on Iterated Local Search (ILS) is presented. Finally, results obtained are statistically analyzed to determine the allocation procedures that accomplish the best results in terms of served demand and used capacity.

Instances description

The objective of this work is to evaluate the impact of the proposed allocation procedures in the amount of demand covered achieved by the metaheuristic ILS when solving the CMCLP.

Two groups of instances (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 Bagherinejad 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 $c_j \approx \alpha * (\sum a_i)/(0{,}5 * |J|)$ following the strategy presented by 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 to allow replication.

Solving the CMCLP test instances by 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. ILS is a metaheuristic frecuently used to solve the MCLP Salari (2014). The CMCLP is modeled and solved as an optimization problem using the framework BiCIAM Fajardo (2015), which provides an implementation of the Iterated Local Search (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 codification scheme of the solution 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 $p = 2$.

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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

Figure 1 - Solution codification example. (Own elaboration)

Initial solution and perturbation procedures

To obtain the initial solution, a greedy-add approach proposed by Church and ReVelle (1974) is used. This consists in opening facilities in descending order, considering the amount of demand that each facility contributes independently.

To explore the solution space a set of four mutation operators is used. They consist in performing exchanges between opened and closed facilities. The first is the 2-swap proposed in 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, proposed by Davari et al. (2013), where the facility selection is made using a roulette constructed by the probability of a facility to cover or not the demand nodes.This approach ensures that 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, proposed in Fazel Zarandi et al. (2013), which follow the same principles as the above operators, but they exchange *k* facilities at the same time.

Results and discussion

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.

To compare the performance of approximated algorithms, non-parametric statistical tests can be applied to justify the conclusions obtained from the analysis, based on Derrac et al. (2011). Therefore, to determine the allocation procedure that obtains the best objective function value (amount of total demand served), the Fried-

man non-parametric test Friedman (1937) and the Holm post-hoc procedure Holm (1979) are applied. These tests were performed using the software KEEL Triguero et al. (2017), with a significance value $\alpha = 0{,}05$.
Since ILS is a non deterministic metaheuristic, it was executed 30 times with 10000 iterations for each instance under the six allocation approaches to obtain the average demand covered. The experiments where performed in a laptop with an Intel Core i5-5200U CPU and 8GB of DDR3-RAM. For each instance the average demand served is analyzed. Average demand served corresponds to average objective function value of the best solution found in each execution, determined by the equation $\sum_{i \in I} \sum_{j \in N_i} a_i Y_{ij}$.
As a result of the experiments, the best average demand coverage is obtained by NFMaxD and RFMaxD, while the worst results are obtained by RFMinD and NFMinD procedures. After applying the Friedman test, a $p-value = 0{,}00$ was obtained, indicating the presence of significant differences among the algorithms respect to the significance level defined as $alpha = 0{,}05$. The allocation approach with the best ranking is NFMaxD, while the worst ranking was obtained by RFMinD.
For the post-hoc procedure, NFMaxD is considered as the control method, presenting significant difference with respect to the other allocation procedures, with the exception of RFMaxD, given that both procedures allocate demand nodes in a descending order. In terms of computational efficiency, in average RF procedures run 12 % faster than NF procedures. Taking this results into account, and the temporal complexity of NF procedures, the best option would be to use RF procedures unless allocating demand nodes to the nearest facility is required.
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 NFMinD 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.

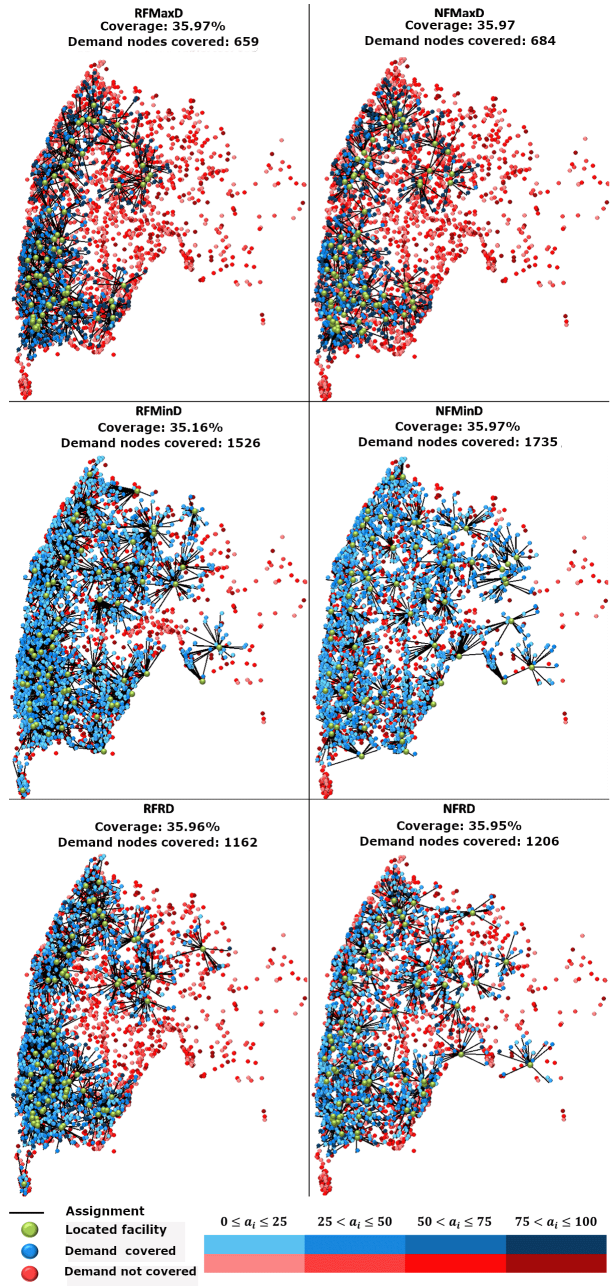

Figure 2 - Representation of obtained solutions by allocation procedure. (Own elaboration)

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 observation 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.
As can be noted, the NFMaxD solution has allocations between demand nodes and facilities with a d_{ij} lower than RFMaxD, obtaining an overall distance(travel time) 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. Another aspect to take into account evaluating the performance of the allocation procedures is the use of the capacity. The highest average of the 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. In spite of the 97 % average capacity usage, there are some instantes where the used capacity of MinD approaches is over 95 %. These observations leads to the hypothesis that allocating demand nodes in an ascending order leads to a inefficient use of the available capacity, since demand nodes with lower weights are allocated first there is no capacity available to allocate medium and high weight demand nodes; therefore this type of allocation achieves a low demand coverage.

Conclusions

In this paper, six demand node allocation procedures for the CMCLP are proposed. These procedures come from the need to better use the use of the limited capacity of facilities in order to maximize the total demand covered. 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. Taking into account time efficiency between NFMaxD and RFMaxD procedures,

it is advisable to use RFMaxD allocation procedure since it achieves the same demand coverage as NFMaxD, with less computational effort.

Bibliographic references

Sajjad Allahi, Mohammadsadegh Mobin, Amin Vafadarnikjoo, and Christian Salmon. An integrated ahp-gis-mclp method to locate bank branches. In *Proceedings of the 2015 Industrial and Systems Engineering Research Conference*, pages 1104–1113, Norcross, Georgia, 2015.

Marvin A Arostegui Jr, Sukran N Kadipasaoglu, and Basheer M Khumawala. An empirical comparison of tabu search, simulated annealing, and genetic algorithms for facilities location problems. *International Journal of Production Economics*, 103(2):742–754, 2006.

J Bagherinejad and M Shoeib. Dynamic capacitated maximal covering location problem by considering dynamic capacity. *International Journal of Industrial Engineering Computations*, 9(2):249–264, 2018.

P V Balakrishnan and J E Storbeck. Mcthresh: Modeling maximum coverage with threshold constraints. *Environment and Planning B: Planning and Design*, 18(4):459–472, 1991. doi: 10.1068/b180459. URL https://doi.org/10.1068/b180459.

CH Chung, DA Schilling, and R Carbone. The capacitated maximal covering problem: A heuristic. In *Proceedings of Fourteenth Annual Pittsburgh Conference on Modeling and Simulation*, pages 1423–1428, 1983.

Richard Church and Charles ReVelle. The maximal covering location problem. *Papers of the Regional Science Association*, 32(1):101–118, 1974. doi: 10.1111/j.1435-5597.1974.tb00902.x.

Richard L Church and Alan Murray. *Location Covering Models: History, Applications and Advancements*. Advances in Spatial Science. Springer International Publishing AG, 1ra edition, 2018.

W. Cook. The traveling salesman problem (tsp). Technical report, Department of Combinatorics and Optimization, University of Waterloo, Available: http://www.math.uwaterloo.ca/tsp/index.html, 2019.

Soheil Davari, Mohammad Hossein Fazel Zarandi, and I Burhan Turksen. A greedy variable neighborhood search heuristic for the maximal covering location problem with fuzzy coverage radii. *Knowledge-Based Systems*, 41:68–76, 2013.

Joaquín Derrac, Salvador García, Daniel Molina, and Francisco Herrera. 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, 2011. ISSN 2210-6502. doi: 10.1016/j.swevo.2011.02.002.

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

Jenny Fajardo, Cynthia Porras, Leydis Sanchez, and Diago E. Estrada. Software tool for model and solve the maximum coverage location problem, a case study: Locations police officers. *Revista de Investigación Operacional (RIO)*, 38(2):141–149, 2017.

Mohammad Hossein Fazel Zarandi, Soheil Davari, and Seyyed Ali Haddad Sisakht. The large-scale dynamic maximal covering location problem. *Mathematical and Computer Modelling*, 57(3-4):710–719, 2013. ISSN 0895-7177. doi: 10.1016/j.mcm.2012.07.028.

M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association*, 32(200):675–701, 1937. doi: 10.2307/3001968.

Ross A. Gerrard and Richard L. Church. Closest assignment constraints and location models: Properties and structure. *Location Science*, 4(4):251–270, 1996. ISSN 0966-8349. doi: https://doi.org/10.1016/S0966-8349(97)00001-6. URL https://www.sciencedirect.com/science/article/pii/S0966834997000016.

Ali Haghani. Capacitated maximum covering location models: Formulations and solution procedures. *Journal of Advanced Transportation*, 30(3):101–136, 1996. doi: 10.1002/atr.5670300308.

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

M. S. Jabalameli, B. Bankian Tabrizi, and M. Moshref Javadi. Capacitated facility location problem with variable coverage radius in distribution system. *IUST*, 21(4):231–237, 2010. URL http://ijiepr.iust.ac.ir/article-1-240-en.html.

Gunhak Lee and Alan T Murray. Maximal covering with network survivability requirements in wireless mesh networks. *Computers, Environment and Urban Systems*, 34(1):49–57, 2010. doi: 10.1016/j.compenvurbsys.2009.05.004.

Alan T Murray, Jing Xu, Zifan Wang, and Richard L Church. Commercial gis location analytics: capabilities and performance. *International Journal of Geographical Information Science*, 33(5):1106–1130, 2019.

Rapeepan Pitakaso and Sombat Sindhuchao. The combination of max-min ant system and iterated local search heuristic for capacitated p-median problem. pages–, November 2021.

Aaron Pulver, Ran Wei, and Clay Mann. Locating aed enabled medical drones to enhance cardiac arrest response times. *Prehospital Emergency Care*, 20(3):378–389, 2016. doi: 10.3109/10903127.2015.1115932.

Majid Salari. An iterated local search for the budget constrained generalized maximal covering location problem. *Journal of Mathematical Modelling and Algorithms in Operations Research*, 13(3):301–313, 2014. ISSN 2214-2495. URL https://doi.org/10.1007/s10852-013-9233-9.

Behzad Bankian Tabrizi, M. Saeed Jabalameli, and Mohammad Moshref Javadi. A simulated annealing method to solve a generalized maximal covering location problem. *International Journal of Industrial Engineering Computations*, 2(2):439–448, 2011. ISSN 1923-2934. doi: 10.5267/j.ijiec.2011.01.003.

Isaac Triguero, Sergio González, Jose M. Moyano, Salvador García, Jesús Alcalá-Fdez, Julián Luengo, Alberto Fernández, Maria José del Jesús, Luciano Sánchez, and Francisco Herrera. Keel 3.0: An open source software for multi-stage analysis in data mining. *International Journal of Computational Intelligence Systems*, 10:1238–1249, 2017. ISSN 1875-6883. doi: https://doi.org/10.2991/ijcis.10.1.82. URL https://doi.org/10.2991/ijcis.10.1.82.

Jing Xu, Alan Murray, Zifan Wang, and Richard Church. Challenges in applying capacitated covering models. *Transactions in GIS*, 24(2):268–290, 2020. ISSN 1361-1682. doi: 10.1111/tgis.12608.

Yanyan Xue, Zongguo Wen, Xiaoli Ji, Hans Th A Bressers, and Chenkai Zhang. Location optimization of urban mining facilities with maximal covering model in gis: A case of china. *Journal of Industrial Ecology*, 21(4):913–923, 2016. doi: 10.1111/jiec.12467.

Conflict of interest

The authors authorize the distribution of this article.

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