

# Online Non-metric Facility Location with Service-Quality Costs

Christine Markarian

Department of Engineering and Information Technology,  
University of Dubai, Dubai, U.A.E.

**Keywords:** Online Non-metric Facility Location, Service-quality Costs, Optimization, Online Algorithms, Competitive Analysis, Randomized Algorithms, Rounding.

**Abstract:** In this paper, we study the *Online Non-metric Facility Location with Service-Quality Costs* problem (Non-metric OFL-SQC), a generalization of the well-known *Online Non-metric Facility Location* problem (Non-metric OFL), in which facilities have, in addition to opening costs, service-quality costs. Service-quality costs are determined by the quality of the service provided by each facility so as the higher the quality, the lower the service-quality cost. These are motivated by companies wishing to incorporate the quality of third-party services into their optimization decisions. Clients are scattered around facilities and arrive in groups over time. Each arriving group is composed of a number of clients at different locations. Non-metric OFL-SQC asks to serve each client in the group by connecting it to an open facility. Opening a facility incurs an *opening cost* and connecting a client to a facility incurs a *connecting cost*, which is the distance between the client and the facility. Moreover, for each group, the algorithm needs to pay the sum of the *service-quality costs* associated with the facilities serving the clients of the group. The aim is to serve each arriving group while minimizing the total facility opening costs, connecting costs, and service-quality costs. We develop the first online algorithm for non-metric OFL-SQC and analyze it using the standard notion of *competitive analysis*, in which the online algorithm's worst-case performance is measured against the optimal offline solution that can be constructed optimally given all the input sequence in advance.

## 1 INTRODUCTION

*Facility Location* problems, that aim to place one or more facilities in a way that meets a given optimization objective, are one of the most well-studied combinatorial optimization problems, with a wide range of applications in operations research, urban planning, management science, economics, marketing, computer science, and many others (Drezner and Hamacher, 2004).

*Facility Location* problems have an online nature, in which the input sequence is revealed in portions over time, and the so-called *online algorithm* reacts to each portion by targeting the given optimization goal. In its most general form, each such sequence is composed of a single client that needs to be connected to an open facility. The online algorithm needs to decide at which locations to open facilities, while minimizing the total facility opening costs and connecting costs or distances between clients and facilities.

*Facility Location* problems are known as *metric* and *non-metric* variants. In the former case, clients and facilities are assumed to reside in the metric space and the distances respect the triangle inequality. The metric properties are normally used in the

analysis of the online algorithms for the metric variants. Both metric (Meyerson, 2001; Fotakis, 2008; Anagnostopoulos et al., 2004) and non-metric (Alon et al., 2006; Markarian, 2021; Markarian et al., 2021; Markarian and auf der Heide, 2019; Markarian and Khallouf, 2021; Markarian and El-Kassar, 2021) variants have been well investigated, in many settings and as many variations.

In this paper, we study an online non-metric variant of *Facility Location*, known as the *Online Non-metric Facility Location With Service-Quality Costs* problem (Non-metric OFL-SQC).

### 1.1 Online Non-metric Facility Location with Service-Quality Costs (Non-metric OFL-SQC)

Given a collection of potential facility locations. Each facility location has an opening cost and a service-quality cost. Service-quality costs are determined by the quality of the service provided by each facility so as the higher the quality, the lower the service-quality cost. These are motivated by companies wishing to incorporate the quality of third-party services

into their optimization decisions. Clients are scattered around facilities and arrive in groups over time. Each arriving group is composed of a number of clients at different locations. Non-metric OFL-SQC asks to serve each client in the group by connecting it to an open facility. Opening a facility incurs the associated facility *opening cost* and connecting a client to a facility incurs a *connecting cost*, which is the distance between the client and the facility. Moreover, for each group, the algorithm needs to pay the sum of the *service-quality costs* associated with the facilities serving the clients of the group. The aim is to serve each arriving group while minimizing the total facility opening costs, connecting costs, and service-quality costs.

## 2 OUR CONTRIBUTION

We design the first online algorithm for non-metric OFL-SQC and measure its performance using *competitive analysis*, a notion commonly used in the analysis of online algorithms (Sleator and Tarjan, 1985; Borodin and El-Yaniv, 2005). An online algorithm is said to be  $c$ -competitive or has competitive ratio  $c$  if its cost is at most  $c$  times that of an optimal solution constructed *offline* given, in advance, all the knowledge about the input sequence, over all possible instances of the problem. The input sequence is given by an adversary that is trying to trick the algorithm so that its competitive ratio is maximized. The algorithm is given each portion of the input and needs to react to it with its eyes closed to the future portions. Hence the only information the algorithm has at any point in time, is the present and the past. Competitive analysis is a worst-case analysis, that can reveal how the algorithm performs against its worst input sequence. Hence, by proving the competitive ratio of the algorithm, one is able to give a provable guarantee about the solution being constructed, in comparison to an optimal solution that could only be constructed given all the input sequence in advance. In our analysis, we assume an *oblivious adversary*, which does not know the random choices made by the algorithm.

### 2.1 Competitive Ratio

We prove that our randomized algorithm for non-metric OFL-SQC has an  $O(\log m \log n)$  competitive ratio, where:

- $m$  is the number of potential facility locations
- $n$  is the total number of clients

### 2.2 Algorithmic Techniques

Our online algorithm for non-metric OFL-SQC draws on ideas from the online algorithms for the *Online Non-metric Facility Location* problem (Alon et al., 2006) and its variant (Markarian, 2021). We first formulate the problem as a directed connectivity graph problem and then run a randomized algorithm based on *randomized rounding*, a technique widely used in the design and analysis of online algorithms.

## 3 OBSERVATIONS ABOUT THE MODEL

It is worth noting that if each arriving portion is composed of a single client, rather than a group of clients, then the problem can be solved as follows. Each client's connecting cost to a facility will be incremented by adding to it the corresponding service-quality cost of the facility. We can then run any online algorithm for the special case of non-metric OFL-SQC, the *Online Non-metric Facility Location* problem (Non-metric OFL) (Alon et al., 2006) to solve this variant.

One might also wonder whether it helps to break down the given portion containing a group of clients into single clients, each arriving as a distinct portion and then adding the service-quality costs as above. However, this is not possible, since, we would then have to pay the service-quality cost of a facility multiple times for the same group of clients and in our model, we assume clients arrive as groups. The groups of clients are motivated by scenarios in which portions represent companies, and each of the clients are the employees of the company. The goal would be to serve each company with the minimum possible service-quality costs of the joint facilities serving the company.

As mentioned earlier, the service-quality costs are motivated by scenarios of companies wishing to take into consideration the quality of the services they are offering through third-party companies when making their decisions. In the classical Facility Location models, the goal is to minimize the total facility opening costs and the distances between the clients and the facilities. Clients are indeed happy when they are served by a nearby facility, but if the service is not up to standard, then this would affect the image of the company. So, the service quality also matters as much as the distance. In many cases, the clients need to be compensated to make up for the poor service. Hence, the company would accompany each facility with a service-quality cost to represent the compensa-

tion costs.

Therefore, the *Online Non-metric Facility Location with Service-Quality Costs* problem (Non-metric OFL-SQC) is motivated by intrinsic client-serving scenarios, in which companies with employees are represented as groups of clients. Each client or employee needs to be connected to an open facility. Facilities are third-party service providers, each associated with an opening cost and a service-quality cost that represents the quality of the service provided by the facility.

Furthermore, the service-quality costs of non-metric OFL-SQC are analogous to the so-called *rating costs* of the *Online Set Cover With Rated Subsets* problem (OSC-RS), which we have recently introduced in (Markarian, 2022). OSC-RS generalizes the *Online Set Cover* problem (Alon et al., 2009), in which we are given a universe of elements and a collection of subsets of the universe, each associated with a subset cost and a rating cost. The algorithm is given, in each step, a request that contains a subset of the elements. To serve a request the algorithm needs to assign it to a number of subsets purchased by the algorithm that jointly cover the requested elements. The algorithm pays the subset costs associated with the subsets purchased and for each request, it pays the sum of the rating costs associated with the subsets assigned to the request. The aim is to serve all requests as soon as revealed, while minimizing the total subset and rating costs paid.

#### 4 LOWER BOUNDS

The *Online Set Cover* problem (OSC) (Alon et al., 2009) is a special case of the *Online Non-metric Facility Location* problem (Non-metric OFL) (Alon et al., 2006), which in turn is a special case of the *Online Non-metric Facility Location with Service-Quality Costs* problem (Non-metric OFL-SQC), in which all service-quality costs are 0.

- There is an  $\Omega\left(\frac{\log n \log m}{\log \log n + \log \log m}\right)$  lower bound on the competitive ratio of any deterministic algorithm for OSC, where  $m$  is the number of subsets and  $n$  is the number of elements, due to (Alon et al., 2009).
- There is an  $\Omega(\log n \log m)$  lower bound on the competitive ratio of any randomized polynomial-time algorithm for OSC, under the assumption that  $BPP \neq NP$ , due to (Korman, 2005).

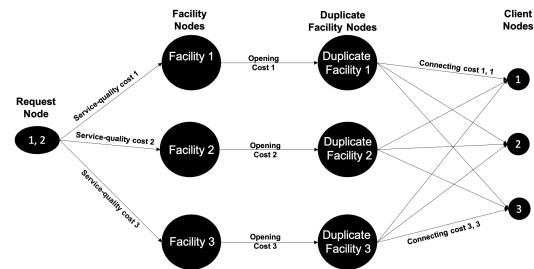


Figure 1: Non-metric OFL-SQC instance of three facilities, three clients, and a request, formulated as a connectivity digraph problem.

#### 5 FORMULATION OF NON-METRIC OFL-SQC AS A CONNECTIVITY DIGRAPH PROBLEM

We formulate a given instance  $I$  of non-metric OFL-SQC as a connectivity digraph problem, as follows. We refer to each group of arriving clients as a *request*. The reader is referred to Figure 1 for an illustration.

$I$  will be represented as a graph  $G = (V, E)$ , where  $V$  denotes the request nodes, the facility nodes, and the client nodes, and  $E$  is a collection of weighted directed edges connecting these nodes.

##### We Construct the Set $V$ of Nodes as Follows:

- For each arriving request, we create a *request node*.
- For each facility  $i$ , we create two facility nodes, namely, *facility node  $i$*  and *duplicate facility node  $i$* .
- For each client, we create a *client node*.

##### We Construct the Set $E$ of Edges as Follows:

- From each request node, we add a directed edge to each facility node, of weight equal to the service-quality cost of the corresponding facility.
- From each facility node, we add a directed edge to its duplicate facility node, of weight equal to the opening cost of the facility.
- From each duplicate facility node, we add a directed edge to each client node, of weight equal to the connecting cost between the client and the corresponding facility.

The facility nodes, the duplicate facility nodes, and the client nodes along with the edges in between are constructed before the execution of the algorithm.

Each request node and its outgoing edges are formed as soon as a request is revealed.

**Upon the Arrival of a New Request:**

- A request node and its edges are added.
- The algorithm outputs, for each client in the request, a directed path from the request node to the corresponding client node.

**Solution Mapping:**

- The algorithm pays each facility opening cost, each service-quality cost, and each connecting cost associated with the edges in the directed paths outputted by the algorithm. The algorithm opens each facility if its facility nodes are in the directed paths of the outputted solution.
- For each client, the algorithm outputs a directed path containing at least one facility node and its duplicate. This is true since every directed path from the request node to the client node contains a facility node and its duplicate node. The algorithm connects each client to the corresponding facility of the directed path.
- According to this mapping, any feasible solution for the transformed instance implies a feasible solution for  $I$ , of the same cost.

## 6 ONLINE ALGORITHM

In this section, we present an online randomized algorithm for the *Online Non-metric Facility Location with Service-Quality Costs* problem (Non-metric OFL-SQC).

The algorithm solves the connectivity digraph problem described in the previous section. It uses an approach similar to that used in other online problems in the literature (Hamann et al., 2018; Markarian, 2021; Alon et al., 2006; Markarian et al., 2021; Markarian, 2018).

### 6.1 Preliminaries

Given the input graph  $G = (V, E)$  with a positive edge-weight function. We refer to the weight of an edge  $e$  by  $w_e$ .

A fraction  $f_e$  is assigned to each edge  $e$  in  $G$ . All fractions are set initially to 0 and will be non-decreasing throughout the run of the algorithm. The *maximum flow* from a node  $u$  to a node  $v$  is the smallest sum of fractions of edges which would disconnect

$u$  from  $v$  if removed. These edges form a *minimum cut*.

The algorithm generates the number  $q$ , independently among  $2 \lceil \log n \rceil$  random variables uniformly distributed in the interval  $[0, 1]$ , where  $n$  is the total number of clients.  $q$  represents the randomized aspect of the algorithm, that will determine which edges will be purchased by the algorithm.

### 6.2 Execution

Given a request node  $r$  at time step  $t$  and a client node  $j$  associated with the request. We let  $S_t$  be the collection of edges of  $G$  outputted by the algorithm *before* and *at* time step  $t$ .

At time step  $t$ :

If the edges in  $S_t$  form a directed path in  $G$  from  $r$  to  $j$ , the algorithm moves on to the next client associated with  $r$ . Else, it performs the following three steps:

**Step 1.** The algorithm checks the maximum flow from  $r$  to  $j$ . While it is less than 1, the algorithm outputs a minimum cut  $Q$  and increases the fraction of each edge in  $Q$ , using the equation below:

$$f_e \leftarrow f_e \left(1 + \frac{1}{f_e}\right) + \frac{1}{|Q| \cdot w_e}$$

**Step 2.** The algorithm adds each edge with fraction above  $q$  (the value generated before the execution of the algorithm) to the solution.

**Step 3.** The algorithm could have outputted a set of edges that form an infeasible solution. To guarantee feasibility, the algorithm performs the following. If  $S_t$  does not contain edges that form a directed path from  $r$  to  $j$ , the algorithm finds a shortest weighted directed path from  $r$  to  $j$  and outputs the edges of this path to the solution.

The three steps of the algorithm are depicted in Algorithm 1 below.

## 7 COMPETITIVE ANALYSIS

In this section, we analyze the competitive ratio of the online algorithm presented above.

Given an instance  $I$  of non-metric OFL-SQC. According to the solution mapping given above, any feasible solution for the graph instance problem corresponding to  $I$  implies a feasible solution for  $I$ , of the same cost.

---

Algorithm 1: Online Algorithm for Non-metric OFL-SQC.

**Step 1.** While the maximum flow from  $r$  to  $j$  is less than 1:

Construct a minimum cut  $Q$  from  $r$  to  $j$  and increase the fraction  $f_e$  of each edge  $e \in Q$ , using the equation below:

$$f_e \leftarrow f_e \left(1 + \frac{1}{w_e}\right) + \frac{1}{|Q| \cdot w_e}$$

**Step 2.** Output each edge  $e$  to the solution if its fraction  $f_e$  is above  $q$ .

**Step 3.** If the edges in  $S_t$  do not form a directed path from  $r$  to  $j$ , output the edges of a smallest weighted directed path from  $r$  to  $j$ .

---

Thus, in order to measure the performance of the algorithm, we analyze the total cost of edges purchased by the algorithm in comparison to the cost of the optimal offline solution.

Let  $Opt$  be the cost of an optimal offline solution. The algorithm purchases edges in steps 2 and 3. Let  $S_1$  and  $S_2$  be the collection of edges purchased by the algorithm in Step 2 and Step 3, respectively. We analyze the expected cost of each step separately.

**Step 2.** In Step 2, the algorithm purchases each edge whose fraction is at least  $q$  (generated before the execution of the algorithm). We fix an edge  $e$  and  $i : 1 \leq i \leq 2 \lceil \log n \rceil$ . We denote by  $X_{e,i}$  the indicator variable to indicate if  $e$  has or has not been purchased by the algorithm. We let  $w_e$  and  $f_e$  be the weight and fraction of edge  $e$ , respectively. The expected cost  $C_{S_1}$  of the collection  $S_1$  of Step 2 can be expressed as follows:

$$C_{S_1} = \sum_{e \in S_1} \sum_{i=1}^{2 \lceil \log n \rceil} w_e \cdot \text{Exp}[X_{e,i}] \quad (1)$$

$$= 2 \lceil \log n \rceil \sum_{e \in S_1} w_e f_e \quad (2)$$

To compare to the edges in the optimal offline solution, we need to understand when the algorithm purchases. We will observe the minimum cuts constructed in Step 1 of the algorithm. Notice that each minimum cut constructed must contain at least one optimal edge. This is because each optimal solution must also contain a directed path to the client at hand.

Let us now observe the number of times a minimum cut is constructed by the algorithm. It is possible to upper bound this number by  $O(Opt \cdot \log |Q|)$ , where  $|Q|$  is the size of the largest minimum cut constructed. We prove this as follows.

*Proof.* Let us fix the edges in the optimal solution. We can prove that each optimal edge appears in a bounded number of minimum cuts. This is true because the fractional value of each such edge eventually reaches 1. After reaching 1, it can't appear in any future minimum cut, as per the algorithm's condition.

Let us observe any optimal edge and the equation of the algorithm. After  $O(w_e \log |Q|)$  fraction increases, the value of the edge reaches at least 1. Recall that, each minimum cut contains at least one optimal edge. Hence,  $O(Opt \cdot \log |Q|)$  minimum cuts must be constructed by the algorithm, where  $|Q|$  is the size of the largest minimum cut constructed.  $\square$

We now give an upper bound on  $|Q|$ . Fix a request node and a client node. Each directed path from the request node to the client node represents one of the facility locations available. Therefore,  $|Q|$  is at most  $m$ , the number of potential facility locations.

Thus, the number of minimum cuts constructed is at most  $O(Opt \cdot \log m)$ .

Next, we show that the total fractional increase accompanying each minimum cut is at most 2.

**Lemma 1.** *Each minimum cut constructed is accompanied with a fractional increase of at most 2.*

*Proof.* We fix a minimum cut  $Q$ . The fraction of each edge  $e$  in  $Q$  is increased by  $w_e \cdot \left(\frac{f_e}{w_e} + \frac{1}{|Q| \cdot w_e}\right)$ , as per the equation in the algorithm. Before fractions increase, the maximum flow was less than 1, as per the algorithm. Thus,  $\sum_{e \in Q} f_e < 1$ . Therefore, we have that:

$$\sum_{e \in Q} w_e \cdot \left(\frac{f_e}{w_e} + \frac{1}{|Q| \cdot w_e}\right) < 2$$

$\square$

Thus,

$$C_{S_1} \leq O(Opt \cdot \log n \cdot \log m) \quad (3)$$

**Step 3.** It remains to bound the expected cost  $C_{S_2}$  of the collection  $S_2$  of edges purchased by the algorithm in Step 3.

The *flow* of a path is the minimum fraction among the edge fractions of a given path. We fix a client node  $u$  and an  $i : 1 \leq i \leq 2 \lceil \log n \rceil$ . We measure the probability that, for a single  $i$ , there is no directed path purchased by the algorithm in Step 2 feasible for  $u$ . In terms of flow, this probability is the probability that  $q$  is more than the flow of each directed path to  $u$ . We let  $Q$  be any minimum cut constructed at the end of Step 2. Before executing Step 3, we had that the sum of flow associated with all directed paths to  $u$  was at least

1 as per the algorithm. Hence, the probability that there is no directed path purchased by the algorithm in Step 2 feasible for  $u$ , for a single  $i$ , is:

$$\prod_{e \in Q} (1 - f_e) \leq e^{-\sum_{e \in Q} f_e} \leq \frac{1}{e}$$

Next, we calculate the probability for all  $i$ :  $1 \leq i \leq 2 \lceil \log n \rceil$  and imply the following. The probability that there is no directed path purchased by the algorithm in Step 2 feasible for  $u$  is at most  $\frac{1}{n^2}$ .

Thus, the algorithm purchases a smallest weighted path from the request node to  $u$  with probability at most  $\frac{1}{n^2}$ . Clearly, this path is upper bounded by Opt, since it is a smallest weighted path.

Since the total number of clients is at most  $n$ , we have that:

$$C_{S_2} \leq n \cdot \frac{Opt}{n^2}$$

Hence, the theorem below follows.

**Theorem 1.** *There is an  $O(\log m \log n)$ -competitive randomized algorithm for the Online Non-metric Facility Location with Service-Quality Costs problem (Non-metric OFL-SQC), where  $m$  is the number of potential facility locations, and  $n$  is the number of clients.*

## 8 CONCLUDING THOUGHTS

In this paper, we have initiated the service-quality costs model by addressing the non-metric variant of *Online Facility Location*. A next step would be to investigate the metric variant in which facilities and clients are assumed to reside in the metric space.

A next research direction is to explore other ways to express service-quality costs. In our model, the service quality of a facility is expressed as a fixed cost, given to the algorithm, and does not change over time. It could be that this quality improves over time and it would be interesting to add this dynamics into the model and study its effect in the competitive ratio of the algorithms.

Our adversary assumes the algorithm has no knowledge at all about the future input portions. One may want to investigate, for instance, other types of adversary and probability distributions for the client arrival.

We have assumed in our model that a client arrives exactly once and this assumption is used in the analysis of the proposed algorithm. In real-world scenarios, one client may appear in more than one group, and a different approach would be needed to solve this variant of the problem.

Finally, it is always interesting to observe how the algorithm performs in simulated or real-world environments. This would give us a better understanding about the performance of the algorithm in average-case scenarios, thus complementing our worst-case scenario analysis.

## REFERENCES

- Alon, N., Awerbuch, B., Azar, Y., Buchbinder, N., and Naor, J. (2006). A general approach to online network optimization problems. *ACM Transactions on Algorithms (TALG)*, 2(4):640–660.
- Alon, N., Awerbuch, B., Azar, Y., Buchbinder, N., and Naor, J. (2009). The online set cover problem. *SIAM Journal on Computing*, 39(2):361–370.
- Anagnostopoulos, A., Bent, R., Upfal, E., and Van Hentenryck, P. (2004). A simple and deterministic competitive algorithm for online facility location. *Information and Computation*, 194(2):175–202.
- Borodin, A. and El-Yaniv, R. (2005). *Online computation and competitive analysis*. Cambridge University Press.
- Drezner, Z. and Hamacher, H. W. (2004). *Facility location: applications and theory*. Springer Science & Business Media.
- Fotakis, D. (2008). On the competitive ratio for online facility location. *Algorithmica*, 50(1):1–57.
- Hamann, H., Markarian, C., auf der Heide, F. M., and Wahby, M. (2018). Pick, pack, & survive: Charging robots in a modern warehouse based on online connected dominating sets. In Ito, H., Leonardi, S., Pagli, L., and Prencipe, G., editors, *9th International Conference on Fun with Algorithms, FUN 2018, June 13-15, 2018, La Maddalena, Italy*, volume 100 of *LIPICs*, pages 22:1–22:13. Schloss Dagstuhl - Leibniz-Zentrum für Informatik.
- Korman, S. (2005). On the use of randomization in the online set cover problem. Master's thesis, Weizmann Institute of Science, Israel.
- Markarian, C. (2018). An optimal algorithm for online prize-collecting node-weighted steiner forest. In Iliopoulos, C. S., Leong, H. W., and Sung, W., editors, *Combinatorial Algorithms - 29th International Workshop, IWOCOA 2018, Singapore, July 16-19, 2018, Proceedings*, volume 10979 of *Lecture Notes in Computer Science*, pages 214–223. Springer.
- Markarian, C. (2021). Online non-metric facility location with service installation costs. In Filipe, J., Smialek, M., Brodsky, A., and Hammoudi, S., editors, *Proceedings of the 23rd International Conference on Enterprise Information Systems, ICEIS 2021, Online Streaming, April 26-28, 2021, Volume 1*, pages 737–743. SCITEPRESS.
- Markarian, C. (2022). Online set cover with rated subsets. In *To appear in the Proceedings of the 24th International Conference on Enterprise Information Systems (ICEIS), 2022, Online Streaming, April 25-27, 2022*.

- Markarian, C. and auf der Heide, F. M. (2019). Online algorithms for leasing vertex cover and leasing non-metric facility location. In Parlier, G. H., Liberatore, F., and Demange, M., editors, *Proceedings of the 8th International Conference on Operations Research and Enterprise Systems, ICORES 2019, Prague, Czech Republic, February 19-21, 2019*, pages 315–321. SciTePress.
- Markarian, C. and El-Kassar, A. N. (2021). Algorithmic view of online prize-collecting optimization problems. In Filipe, J., Smialek, M., Brodsky, A., and Hammoudi, S., editors, *Proceedings of the 23rd International Conference on Enterprise Information Systems, ICEIS 2021, Online Streaming, April 26-28, 2021, Volume 1*, pages 744–751. SCITEPRESS.
- Markarian, C., Kassar, A., and Yunis, M. M. (2021). An algorithmic approach to online multi-facility location problems. In Parlier, G. H., Liberatore, F., and Demange, M., editors, *Proceedings of the 10th International Conference on Operations Research and Enterprise Systems, ICORES 2021, Online Streaming, February 4-6, 2021*, pages 29–35. SCITEPRESS.
- Markarian, C. and Khallouf, P. (2021). Online facility service leasing inspired by the covid-19 pandemic. In *18th International Conference on Informatics in Control, Automation and Robotics, ICINCO 2021*, pages 195–202.
- Meyerson, A. (2001). Online facility location. In *Proceedings 42nd IEEE Symposium on Foundations of Computer Science*, pages 426–431. IEEE.
- Sleator, D. D. and Tarjan, R. E. (1985). Amortized efficiency of list update and paging rules. *Commun. ACM*, 28(2):202–208.