An Approximation Algorithm for a Facility Location Problem with Inventories and Stochastic Demands

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Abstract. In this article we propose, for any $\epsilon > 0$, a $2(1+\epsilon)$-approximation algorithm for a facility location problem with stochastic demands. At open facilities, inventory is kept such that arriving requests find a zero inventory with (at most) some pre-specified probability. The incurred costs are the expected transportation costs from the demand points to the facilities, the operating costs of the facilities and the investment in inventory.

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1 Introduction

Facility location problems have been extensively studied in the OR literature. In a facility location problem, we are given a set of demand points and a set of location where facilities may be opened. The goal is to decide at which location to open facilities and how to assign demand points to facilities such that the total cost of opening facilities and of connecting demand points to facilities is minimized. Variants of this problem can be formulated if one imposes requirements on the set of open facilities or on the assignment of demand points to facilities [1]. Examples of such requirements are a maximum number of facilities that may be opened, a maximum demand that may be served by a facility, or a maximum travel distance from a demand point to an open facility. The facility location problem with its variants has proved to be a very useful tool in modeling many network design or location problems, such as location of plants or warehouses [1, 2] and placement of caches [3].

In this paper we study a variant of the facility location problem where at demand points a stochastic number of requests for items is generated. At open facilities, inventory is kept and, if possible, requests for items are fulfilled immediately. However, since the number of requests is random, it may occur that there is no inventory at the arrival of a request and the request has to be cancelled.

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An arbitrary request arriving at a facility, should only have a (pre-specified) small probability of being lost. We are interested in the relationship between the problem with stochastic demands and inventory and known facility location problems, in particular from the perspective of approximation algorithms.

We will call a ρ-approximation algorithm a polynomial time algorithm that always finds a feasible solution with **objective function value** within ρ times the optimum. The value ρ is called the *performance (approximation) guarantee* of the algorithm.

The majority of facility location problems for which approximation algorithms are known, are deterministic. The simplest version of a facility location problem, *the metric uncapacitated facility location problem* (UFLP), that is the facility location problem with no restrictions on the facilities or the assignment of demand points and with the transportation costs being a metric, is known to be NP-hard. If the transportation costs are unrestricted, approximating the UFLP is as hard as approximating set cover, and therefore cannot be done better than $O(\log n)$ factor, unless $\mathbf{NP} \subseteq \tilde{\mathbf{P}}$. In this article, we assume, for all the facility locations mentioned, that the transportation costs form a metric. The currently known best performance guarantee for the UFLP is 1.52, due to Mahdian, Ye and Zhang [4]. Guha and Khuller [5] and Sviridenko [6] have proved that a better factor than 1.463 for the UFLP is not possible unless $\mathbf{NP} \subseteq \tilde{\mathbf{P}}$.

The problem in which each facility has a certain capacity, but more facilities may be opened at a location if the demand exceeds the capacity of one facility, is known as the *soft capacitated* facility location problem. The best approximation algorithm for this problem has an approximation ratio of 2 and was proposed by Mahdian, Ye and Zhang in [7]. In [8] the authors propose a 1.861-approximation algorithm for the variant in which the cost of facilities are concave functions of the number of demand points served. For the *hard capacitated* facility location problem with splittable demands, where each facility has a certain capacity, only one facility may be open at a location and a demand point may be served by several locations, the best approximation algorithm is due to Zhang, Chen and Ye [9], and achieves an approximation ratio between $3+2\sqrt{2}-\epsilon$ and $3+2\sqrt{2}+\epsilon$, for any given constant $\epsilon > 0$.

Stochastic facility location problems (problems where the demand is stochastic or/and the service offered by facilities is of stochastic nature) were mainly treated in the OR literature [10, 11, 12, 13, 14]. Several heuristics have been proposed to obtain solutions for these problems. To the best of our knowledge, the first approximation algorithm for a stochastic facility location problem was proposed by Ravi and Sinha in [15] and improved by Mahdian in [16]. The latest algorithm is based on the primal-dual technique and has a 3-approximation guarantee. Their approach is scenario-based, i.e. in each scenario all the data are known, including the probability with which each scenario takes place.

The paper is organized as follows. In section 2 we describe the stochastic facility location problem in more detail and formulate it such that it can be reduced to a soft capacitated facility location problem. Based on this reduction, we then propose in Section 3, a $2(1+\epsilon)$-approximation algorithm for our problem. We conclude the section by showing that the same ideas can be applied for designing approximation algorithms for a larger class of problems. Finally, we present some conclusions and remarks on the stochastic facility location problem we have analyzed.

2 The Facility Location Problem with Stochastic Demands

In this section we describe in more detail the stochastic facility location problem in which we are interested. There is a set of demand points $D, |D| = N$ at which requests are generated, and a set of locations, $F, |F| = K$, where facilities may be opened. We assume that the requests at a demand point $j \in D$ are generated according to a Poisson process, independent of the processes at other demand points in D. At each open facility an inventory is kept such that an arriving request finds a zero inventory (and is lost), with probability at most α. We then say that $(1 - \alpha)$ is the *fill rate* of the system . The inventories at the open facilities are restored only at fixed points in time and the period between two such points is called a *reorder period*. The holding cost per unit of inventory at an open facility $i \in F$ is c_i and the cost of keeping a facility open at location $i \in F$ during a reorder period is f_i. The transportation cost per unit of demand from facility $i \in F$ to demand point $j \in D$ is c_{ij}. We assume that the transportation costs are proportional to the distances and form a metric.

The goal is to decide at which locations to open facilities, the level of inventory to be installed at each open facility and how to assign demand points to facilities such that the fill rate is at least $1 - \alpha$ and the average total cost per reorder period is minimized.

Let X_j denote the number of generated requests at demand point j during a reorder period and let $\lambda_j = E(X_j)$. Denote by V_i the inventory order up to level at facility $i \in F$, i.e. the inventory level at the beginning of a reorder period. Let y_i, respectively x_{ij}, be $0 - 1$ variables indicating if a facility at location $i \in F$ is open, respectively if demand point $j \in D$ is assigned to a facility $i \in F$. The facility location problem with stochastic demands given above, is fully described by the following integer program:

$$\min \sum_{i \in F} (f_i + c_i V_i) y_i + \sum_{j \in D} \sum_{i \in F} \lambda_j c_{ij} x_{ij} \tag{1}$$

$$\text{s.t. } x_{ij} \le y_i, \qquad i \in F, \quad j \in D, \tag{2}$$

$$\sum_{i \in F} x_{ij} = 1, \qquad j \in D, \tag{3}$$

$$\mathrm{P}\begin{pmatrix}\text{an arbitrary arriving requests at} \\ \text{facility } i \text{ is lost}\end{pmatrix} \le \alpha, \quad i \in F, \tag{4}$$

$$x_{ij}, y_i \in \{0, 1\}, \qquad i \in F, \quad j \in D. \tag{5}$$

The first term in the objective function includes the costs for keeping facilities open and for the maximum inventory at the facilities during a reorder period, while the second term is the expected transportation cost during such a period. Constraints (2), (3) and (5) guarantee that each demand point is assigned to exactly one open facility and constraints (4) guarantee that the fill rate attained at each open location will be at least $1 - \alpha$.

Next we will give an equivalent formulation of constraints (4). Let $\tilde{X}_i$ be the total demand assigned to location i. Clearly, $\tilde{X}_i = \sum_{j \in D} x_{ij} X_j$. Since the requests generated at demand points during reorder periods are independent Poisson distributed random variables, $\tilde{X}_i$ has a Poisson distribution with mean $\mathrm{E}(\tilde{X}_i) = \sum_{j \in D} x_{ij} \lambda_j$. From the theory of regenerative processes (see e.g. [17]), it follows that for location i, the following holds:

$$\mathrm{P}\begin{pmatrix}\text{an arbitrary arriving requests at} \\ \text{facility } i \text{ is lost}\end{pmatrix} = \frac{\mathrm{E}((\tilde{X}_i - V_i)^+)}{\mathrm{E}(\tilde{X}_i)}, \tag{6}$$

where $(a)^+ = \max(0, a)$. Condition (4) can be rewritten as

$$\mathrm{E}((\tilde{X}_i - V_i)^+) \le \alpha \mathrm{E}(\tilde{X}_i). \tag{7}$$

For a Poisson distributed random variable Y with $E(Y) = \lambda$, define the inventory $V_\alpha(\lambda)$ by

$$V_\alpha(\lambda) = \min\{n | E((Y - n)^+) \le \alpha\lambda\}. \tag{8}$$

Using (7) and (8), our problem can be reformulated as

$$(\mathbf{P}) \quad \begin{aligned} \min & \sum_{i \in F} (f_i + c_i V_\alpha(\sum_{i \in F} x_{ij} \lambda_j)) y_i + \sum_{j \in D} \sum_{i \in F} \lambda_j c_{ij} x_{ij} \\ \text{s.t. } & x_{ij} \le y_i, && i \in F, \quad j \in D, \\ & \sum_{i \in F} x_{ij} = 1, && j \in D, \\ & x_{ij}, y_i \in \{0, 1\}, && i \in F, \quad j \in D. \end{aligned}$$

Note that constraints (4) have moved into the objective function. This will enable us to further reduce the problem to a soft capacitated facility location problem, for which approximation algorithms are known (see e.g. [7]). In the remainder of the paper we will present this reduction in detail.

3 A $2(1 + \epsilon)$-Approximation Algorithm for the Stochastic Facility Location Problem

For a facility location problem (P), an instance $\mathcal{I}$ and a feasible solution $\mathcal{S}$ we denote by $cost_{F,\mathcal{I}(P)}(\mathcal{S})$ the cost of opening facilities and by $cost_{T,\mathcal{I}(P)}(\mathcal{S})$ the transportation cost incurred by $\mathcal{S}$. For the sake of simplicity, we will omit to mention the instance.

Definition 1. *We call a polynomial time reduction $\mathcal{R}$ from facility location problem P_1 to P_2 a (σ_F, σ_T)-reduction if $\mathcal{R}$ maps an instance $\mathcal{I}$ of P_1 to an instance $\mathcal{R}(\mathcal{I})$ of P_2 and it has the following properties:*

a) For any feasible solution $\mathcal{S}_1$ for the instance $\mathcal{I}$ of P_1 there is a corresponding solution $\mathcal{S}_2$ for the instance $\mathcal{I}$ of P_2 with

$$cost_{F,P_2}(\mathcal{S}_2) \leq \sigma_f \, cost_{F,P_1}(\mathcal{S}_1),$$

and

$$cost_{T,P_2}(\mathcal{S}_2) \leq \sigma_c \, cost_{T,P_1}(\mathcal{S}_1).$$

b) For any feasible solution $\mathcal{S}_2$ for the instance $\mathcal{R}(\mathcal{I})$ of P_2, there is a feasible solution $\mathcal{S}_1$ for the instance $\mathcal{I}$ of P_1 with

$$cost_{F,P_1}(\mathcal{S}_1) + cost_{T,P_1}(\mathcal{S}_1) \leq cost_{F,P_2}(\mathcal{S}_2) + cost_{T,P_2}(\mathcal{S}_2).$$

Definition 2. *An algorithm is called an (α, β)-approximation algorithm for a facility location problem (P), if for any instance $\mathcal{I}$ of (P), and for any solution $\mathcal{S}$ for $\mathcal{I}$ the cost of the solution found by the algorithm is at most $\alpha \, cost_{F,P}(\mathcal{S}) + \beta \, cost_{T,P}(\mathcal{S})$.*

Remark 1. Note that combining a (σ_F, σ_T)-reduction from P_1 to P_2 and an (α, β)-approximation algorithm for P_2 gives an $(\alpha\sigma_F, \beta\sigma_T)$-approximation algorithm for P_1. Moreover, the approximation guarantee of the algorithm for P_1 is $\max\{\alpha\sigma_F, \beta\sigma_T\}$.

The construction of a $2(1+\epsilon)$-approximation algorithm for $(\mathbf{P})$, consists of several steps. First we will study the inventory function $V_\alpha(\lambda)$ given by (8). Based on it's properties, we propose a $(2,1)$-reduction of $(\mathbf{P})$ to a soft capacitated facility location problem, named $(\mathbf{SP_2})$. Finally, we describe a refined soft capacitated problem, $(\mathbf{SP_{1+\epsilon}})$ to which $(\mathbf{P})$ can be $(1+\epsilon, 1)$-reduced and show that this gives $2(1+\epsilon)$-approximation algorithm for $(\mathbf{P})$.

Lemma 1. *The function $V_\alpha(\lambda)$ satisfies*

$$V_\alpha(\lambda_1 + \lambda_2) \leq V_\alpha(\lambda_1) + V_\alpha(\lambda_2).$$

Proof. Suppose that two independent Poisson streams with rate λ_1, respectively λ_2, arrive at a location i and that the inventory level at location i is $V_\alpha(\lambda_1) + V_\alpha(\lambda_2)$. Let Y_1 and Y_2 be the number of arrivals in the first, respectively in the second stream. Since

$$(Y_1 + Y_2 - (V_\alpha(\lambda_1) + V_\alpha(\lambda_2)))^+ \leq (Y_1 - V_\alpha(\lambda_1))^+ + (Y_2 - V_\alpha(\lambda_2))^+,$$

it is readily seen that

$$\begin{aligned} &\mathrm{E}(Y_1 + Y_2 - (V_\alpha(\lambda_1) + V_\alpha(\lambda_2)))^+ \\ &\qquad \leq \mathrm{E}(Y_1 - V_\alpha(\lambda_1))^+ + \mathrm{E}(Y_2 - V_\alpha(\lambda_2))^+ \leq \alpha(\lambda_1 + \lambda_2). \end{aligned}$$

Hence, $V_\alpha(\lambda_1 + \lambda_2) \leq V_\alpha(\lambda_1) + V_\alpha(\lambda_2)$. □

Remark 2. Note that $V_\alpha(\lambda)$ is a step function, thus not concave. Therefore we cannot directly use the procedure proposed in Mahdian and Pal [18], for solving the facility location problem with concave facility cost functions. Moreover, not even the length of the steps is increasing as function of the height, where the length of a step at level n is defined as $\sup\{\lambda | V_\alpha(\lambda) = n\} - \inf\{\lambda | V_\alpha(\lambda) = n\}$. For example, numerical experiments show that, when $\alpha = 0.1$, the length of the steps is increasing up to level 40 and decreasing above this level.

Next we present a reduction of $(\mathbf{P})$ to a soft capacitated facility location problem, which we denote by $(\mathbf{SP_2})$. The demand points, their requests and facility locations are the same as in problem $(\mathbf{P})$. Let $M = \lceil \log_2(V_\alpha(\sum_{j\in D} \lambda_j)) \rceil$ and let $L = \{1, \cdots, M\}$. We define M types of facilities with capacities $u_\ell = \max\{\lambda | V_\alpha(\lambda) \le 2^\ell\}$, respectively. A facility of type l at location i is denoted by (i, l) and has corresponding cost $f_{il} = f_i + c_i 2^\ell$. At each location $i \in F$, M facilities may be opened.

Let the 0-1 variables y_{il}, x_{ilj}, indicate whether a facility of type l is opened at location i, respectively whether demand point j is assigned to facility (i, l). Then, $(\mathbf{SP_2})$ can be formulated as the integer program:

$$(\mathbf{SP_2}) \quad \begin{aligned} \min \sum_{j\in D}\sum_{i\in F}\sum_{\ell\in L} \lambda_j c_{ij} x_{i\ell j} &+ \sum_{i\in F}\sum_{\ell\in L} f_{i\ell} y_{i\ell} \\ \text{s.t.} \sum_{j\in D} \lambda_j x_{i\ell j} \le u_\ell y_{i\ell}, &\qquad i\in F, \quad \ell \in L, & (9) \\ \sum_{i\in F}\sum_{\ell\in L} x_{i\ell j} = 1, &\qquad j \in D, & (10) \\ x_{i\ell j}, y_{i\ell} \in \{0,1\}, &\qquad i\in F, \quad j \in D, \quad \ell\in L. & (11) \end{aligned}$$

Constraints (9), (10) and (11) insure that each demand point is assigned to one open facility and that no more than demand u_ℓ is assigned to a facility of type ℓ.

Remark 3. Note that although formulated as a hard capacitated facility location problem ($y_{il} \in \{0, 1\}$), problem $(\mathbf{SP_2})$ is a soft capacitated problem. Suppose that we relax the y variables to be integer. Consider first a $k < M$. The optimal solution of the relaxed version will not choose to open two facilities of type k at a location, since opening a facility of type $k + 1$ is cheaper and has, at least, the same capacity as two facilities of type k. Since one facility of type M can handle all the demand, there will be always at most one facility of type M open in the optimal solution of the relaxed version of $(\mathbf{SP_2})$. Thus, $(\mathbf{SP_2})$ is a soft capacitated facility location problem.

In the following lemma we describe a $(2, 1)$-reduction of $(\mathbf{P})$ to $(\mathbf{SP_2})$.

Lemma 2.
(i) For each feasible solution $(\tilde{x}, \tilde{y})$ of $(\mathbf{P})$ with facility cost $cost_{F,\mathbf{P}}(\tilde{x}, \tilde{y})$ and transportation cost $cost_{T,\mathbf{P}}(\tilde{x}, \tilde{y})$ there exists a feasible solution (x, y) of $(\mathbf{SP_2})$ with $cost_{F,\mathbf{SP_2}}(x, y) \le 2cost_{F,\mathbf{P}}(\tilde{x}, \tilde{y})$ and $cost_{T,\mathbf{SP_2}}(x, y) = cost_{T,\mathbf{P}}(\tilde{x}, \tilde{y})$.

(ii) For each feasible solution (x, y) *of* $(\mathbf{SP_2})$*, there exists a feasible solution* $(\tilde{x}, \tilde{y})$ *of* $(\mathbf{P})$ *of lower cost.*
(iii) There exists a $(2, 1)$*-reduction of* $(\mathbf{P})$ *to* $(\mathbf{SP_2})$ *.*

Proof. (i) Consider a solution $(\tilde{x}, \tilde{y})$ of $(\mathbf{P})$. For $i \in F$ with $\tilde{y}_i = 1$ and $\ell \in L$ define $\ell_i = \min\{n | \sum_{j\in D} \tilde{x}_{ij}\lambda_j \le u_n\}$, set $y_{i\ell} = 1$ for $\ell = \ell_i$, set $y_{i\ell} = 0$ otherwise and set $x_{i\ell j} = \tilde{x}_{ij} y_{i\ell}$ for $j \in D$. For each $i \in F$ with $\tilde{y}_i = 0$, set $x_{i\ell j} = y_{i\ell} = 0$ for $j \in D$ and $\ell \in \{1, \cdots, M\}$ and define $\ell_i = 1$. It can readily be seen that (x, y) is a feasible solution of $(\mathbf{SP_2})$ with associated costs

$$\begin{aligned} \text{cost}_{T,\mathbf{SP_2}}(x, y) &= \sum_{i\in F}\sum_{j\in D}\sum_{\ell\in L} \lambda_j c_{ij} x_{i\ell j} = \sum_{i\in F}\sum_{j\in D} \lambda_j c_{ij} \tilde{x}_{ij} \\ &= \text{cost}_{T,\mathbf{P}}(\tilde{x}, \tilde{y}) \end{aligned}$$

and

$$\begin{aligned} \text{cost}_{F,\mathbf{SP_2}}(x, y) &= \sum_{i\in F}\sum_{\ell\in L} f_{i\ell} y_{i\ell} = \sum_{i\in F} (f_i + 2^{\ell_i}) y_{i\ell_i} \\ &\le 2\text{cost}_{F,\mathbf{P}}(\tilde{x}, \tilde{y}), \end{aligned}$$

where the inequality follows from the definitions of ℓ_i and u_n.

(ii) For each feasible solution (x, y) of $(\mathbf{SP_2})$, define the vector $(\tilde{x}, \tilde{y})$ by $\tilde{x}_{i,j} = \max_{\ell\in\{1,\cdots,M\}}\{x_{i\ell j}\}$ and $\tilde{y}_i = \max_{\ell\in\{1,\cdots,M\}}\{y_{i\ell}\}$. Clearly, $(\tilde{x}, \tilde{y})$ is a feasible solution for $(\mathbf{P})$. Moreover, from Lemma 1 follows that $V_\alpha(\sum_{j\in D} \tilde{x}_{ij}\lambda_j) \le \sum_\ell v_\ell y_{i\ell}$ and so $(\tilde{x}, \tilde{y})$ has a lower cost than the one incurred by (x, y) for $(\mathbf{SP_2})$.

(iii) Follows from (i) and (ii) of this lemma. □

In the following, we prove that one can obtain a $(1 + \epsilon, 1)$-reduction between $(\mathbf{P})$ and a slightly modified version of $(\mathbf{SP_2})$ by the same reasoning as in Lemma 2. We define this modified version $(\mathbf{SP_{1+\epsilon}})$ as follows.

Define for $\epsilon > 0$ the integer sequence $\tilde{v}_{0,0} = 0$; $v_{m0} = \lfloor(1+\epsilon)(1+v_{m-1,0})\rfloor$ and $v_{mk} = 2^k v_{m0}$ for $m = 1, 2, \cdots$ and $k = 0, 1, \cdots$. Next, define the integer sequence $v_0 = 0$ and $v_\ell = \min\{\tilde{v}_{mk} > v_{\ell-1} | m = 1, 2, \cdots \text{ and } k = 0, 1, \cdots\}$ for $\ell = 1, 2, \cdots$ and define $M = \min\{\ell | v_\ell \ge V_\alpha(\sum_{j\in D} \lambda_j)\}$. Since $\tilde{v}_{m0} \ge (1+\epsilon)v_{m-1,0}$, it is easy to find that, for $\epsilon \in (0, 1)$,

$$M \le \lceil \log_{(1+\epsilon)}(V_\alpha(\sum_{j\in D} \lambda_j)\rceil \lceil \log_2(V_\alpha(\sum_{j\in D} \lambda_j)\rceil \le \frac{4}{\epsilon}\lceil \log_2(V_\alpha(\sum_{j\in D} \lambda_j)\rceil^2.$$

Furthermore, from the construction of the sequence v_ℓ, we see that $(1 + v_\ell) \le v_{\ell+1} \le (1+\epsilon)(1+v_\ell)$. Consider a facility location problem with the same demand points, requests and facility locations as in problem $(\mathbf{P})$. At each location $i \in F$, M facilities may be opened, $(i, 1), ...(i, M)$, of costs $f_i + c_i v_\ell$ and capacities $u_\ell = \max\{\lambda | V_\alpha(\lambda) \le v_\ell\}$.

Let the 0-1 variables y_{il}, x_{ilj}, indicate whether a facility of type l is opened at location i, respectively whether demand point j is assigned to facility (i, l). Then, $(\mathbf{SP_{1+\epsilon}})$ can be formulated as an integer program similar to $(\mathbf{SP_2})$.

As in Remark 3, we note that although formulated as a hard capacitated facility location problem, $(\mathbf{SP_{1+\epsilon}})$ is in fact a soft capacitated facility location problem. In order to show this, we prove that, even if we allow more facilities of the same type to be opened at a location, at most one will be opened in the optimal solution. Assume that in the optimal solution, at least one facility of type k at location i is opened. If the cost of facility (i,k) exceeds $f_i + c_i V_\alpha(\lambda)/2$, then opening facility (i,M) (which can handle all demands) is cheaper than opening two facilities (i,k). If the costs of facility (i,k) equals $f_i + c_i v_k$ with $v_k \leq V_\alpha(\lambda)/2$, we see, by the definition of the sequence v_ℓ, that there is also a facility (i,k') with cost $f_i + 2c_i v_k$. By Lemma 1, the capacity of a type k' facility is at least twice the capacity of a type k facility. Hence, in the optimal solution of the relaxed problem of $(\mathbf{SP_{1+\epsilon}})$, at every location at most one facility of type k is opened. Thus, $(\mathbf{SP_{1+\epsilon}})$ is a soft capacitated facility location problem.

Lemma 3. *For any $\epsilon > 0$, the problem $(\mathbf{P})$ can be $(1+\epsilon, 1)$-reduced to $(\mathbf{SP_{1+\epsilon}})$.*

Proof. We follow the proof of Lemma 2. Consider a feasible solution $(\tilde{x}, \tilde{y})$ of $(\mathbf{P})$ and construct a feasible solution (x, y) of $(\mathbf{SP_{1+\epsilon}})$ as follows. Open facility (i, ℓ) at location i only if $\sum_{j \in D} \tilde{x}_{ij} = 1$ and $\ell = \min\{n | \sum_{j \in D} \tilde{x}_{ij} \lambda_j \leq u_n\}$. Since the inventory levels are discrete and $\sum_{j \in D} \tilde{x}_{ij} \lambda_j > u_{\ell-1}$, the inventory at location i satisfies $V_\alpha(\sum_{j \in D} x_{ij} \lambda_j) \geq 1 + v_{\ell-1}$ and therefore the cost of opening facilities in $(\mathbf{SP_{1+\epsilon}})$ is at most $(1+\epsilon)$ times the facility costs in $(\mathbf{P})$.

Now consider a solution (x, y) of $(\mathbf{SP_{1+\epsilon}})$ and construct a corresponding solution $(\tilde{x}, \tilde{y})$ of $(\mathbf{P})$ by $\tilde{x}_{i,j} = \max_{\ell \in \{1, \cdots, M\}} \{x_{i\ell j}\}$ and $\tilde{y}_i = \max_{\ell \in \{1, \cdots, M\}} \{y_{i\ell}\}$. As in Lemma 2, one can show that $(\tilde{x}, \tilde{y})$ is a feasible solution with the same transportation cost as the one incurred by (x, y) and with less opening facility cost than the one incurred by (x, y). □

Theorem 1. *There is a $2(1+\epsilon)$-approximation algorithm for the facility location problem with stochastic demands $(\mathbf{P})$.*

Proof. Problem $(\mathbf{SP_{1+\epsilon}})$ is a soft capacitated facility location problem with general demands. For the soft capacitated facility location problem with unit demands, a (2,2)-approximation algorithm was proposed in [7]. It can easily be shown that their analysis also applies for general demands, thus implying a (2,2)-approximation algorithm for $(\mathbf{SP_{1+\epsilon}})$. The existence of a (2,2)-approximation algorithm for $(\mathbf{SP_{1+\epsilon}})$, implies, by Lemma 3 and Remark 1, the existence of a $2(1+\epsilon)$-approximation algorithm for the stochastic facility location problem $(\mathbf{P})$. □

Generalization. At the basis of our algorithm lies the property that, for two demand points j and j', with demand λ_j, respectively $\lambda_{j'}$, the inventory which has to be installed at a facility satisfies $V_\alpha(\lambda_j + \lambda_{j'}) \leq V_\alpha(\lambda_j) + V_\alpha(\lambda_{j'})$, i.e., it is more profitable to look at the joint demand than to treat the demands separately. It is easy to see that the same analysis holds for the metric UFLP with the cost of opening facilities depending on the amount served by a facility and satisfying $f_i(\lambda_j + \lambda_{j'}) \leq f_i(\lambda_j) + f_i(\lambda_{j'})$, for each $i \in F$ and $j, j' \in D$. Clearly, concave facility costs have this property.

Remark 4. The same technique can also be used for the following version of the facility location problem with stochastic demands: at facilities an arbitrary number of servers can be placed, which all work at equal speed. At each facility, there is an upperbound on the expected waiting time of a customer. The incurred costs are the transportation costs and the facility costs; the cost of a facility is the sum of the opening cost and the cost for installing servers, which is linear in the number of installed servers.

We model a facility as an $M/M/k$ queue, that is a queue with k servers and exponential interarrival and service times. Without loss of generality, we assume that the expected service time is 1. Let $WT(M_\lambda/M/k)$ denote the expected waiting time at such a queue with arrival rate λ. At an open facility i with arrival rate Λ_i and ki servers, the constraint on the waiting time then is $WT(M_{\Lambda_i}/M/ki) \leq \tau$ for some pre-specified τ. An explicit expression for this expectation can be found in e.g. [19], page 71 Define $N_\tau(\lambda) = \min\{k|WT(M_\lambda/M/k) \leq \tau)$. It can be shown that $N_\tau(\lambda_1 + \lambda_2) \leq N_\tau(\lambda_1) + N_\tau(\lambda_2)$. Thus, applying a similar reduction as the one described in this section, one obtains a $2(1+\epsilon)$-approximation algorithm for this problem as well.

4 Conclusions

In this paper we have introduced a facility location problem with inventory and stochastic demands. We proposed a $2(1 + \epsilon)$-approximation algorithm for this model by giving both a $(1 + \epsilon, 1)$-reduction to a soft capacitated facility location problem with general demands and a $(2, 2)$-approximating algorithm for this soft capacitated facility location problem. The same analysis is applied for approximating more general problems.

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