# MULTI-FACILITY LOCATION PROBLEM WITH NONINCREASING PIECEWISE LINEAR DEMAND ON A TREE 

Masashi Umezawa Hisakazu Nishino<br>Keio University

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#### Abstract

This paper deals with a multi-facility location problem on a tree. Given the number of facilities and the tree structure, the problem is to find the optimal locations of facilities so as to maximize the service provider's gain obtained from customers accessing the nearest facility. Customers are located only at vertices of the tree. For each vertex, customers' demand function is given, which is nonincreasing piecewise linear in the distance from the vertex to the nearest facility location. We modify the algorithm proposed by Megiddo-Zemel-Hakimi (1983), and show that it yields the exact optimum within a polynomial time.


## 1. Introduction

The problem of facility location arises in many different contexts such as information networks, logistic systems, and retail chain stores. The importance of efficient optimization methods for this problem can never be overemphasized. Unfortunately, the multi-facility location problem on a network including cycles is $\mathcal{N} \mathcal{P}$-hard.

Multi-facility location problems on a network have been studied since the appearance of Hakimi [2] (see also Hakimi [3]). They are known as a $p$-median problem and $p$-center problem (see Tancel, Francis, and Lowe [9]). Matula and Kolde [6] and Kariv and Hakimi [5] presented polynomial time algorithms for the problems on a tree network. Megiddo, Zemel, and Hakimi [7] developed a polynomial time algorithm for the location problem of multiple facilities on a tree, given the constant demand function with a finite support for each vertex.

In this paper, the $p$-median problem and the problem by Megiddo et al. [7] are extended by introducing a nonincreasing piecewise linear demand function at each vertex. Customers are located only at vertices of a tree. Associated with each vertex is a demand function, which is a nonincreasing piecewise linear function of the distance from the vertex to the nearest facility. When the trip distance exceeds a certain limit (the maximum trip distance), the demand vanishes. For a given number $p$ of facilities, a service provider aims at finding locations of facilities to maximize the total gain obtained from the customers accessing the facilities.

The facilities may be established anywhere on the network. We prove, however, that the locations of facilities can be restricted to a polynomial number of points on the network. Then we develop an algorithm for the problem with nonincreasing piecewise linear demand functions that yields an optimal solution within a polynomial time. Our algorithm is based on the method proposed by Megiddo et al. [7].

Megiddo et al. [7] state that the optimal gain function is concave in the number of facilities. This statement, however, is not valid in general. We show a simple example exhibiting that their algorithm does not yield an optimal solution. The assumption of the
concavity appears to bring about this failure. We make a modification to their algorithm, which enables us to attain an optimal solution in their model as well.

In Section 2, we formally describe a location problem on a tree with multiple facilities, and propose a new algorithm to compute an optimal solution. In Section 3, we show that the gain function is not necessarily concave through a simple example. Finally, in Section 4 , some concluding remarks are given.

## 2. Multi-Facility Location Problem

### 2.1. Model

Consider a tree $T=(V, E)(|V|=n,|E|=n-1)$, where $V$ denotes the set of vertices and $E$ the set of edges. Tree $T$ can be embedded in Euclidean plane. For notational simplicity, this embedded set is also denoted by $T$. Let $V=\{1, \ldots, n\}$, and $e \in E$ connecting $i, j \in V$, $1 \leq i<j \leq n$, be represented by the closed interval $[i, j]$. The length of an edge $[i, j] \in E$ is represented by $d_{i j}$. For every pair of points $x, y \in T$, let $d(x, y)(=d(y, x))$ be the length of the path connecting $x$ with $y$. We associate a set $C_{i}$ of customers with each $i \in V$. For each $C_{i}$, the customers' demand is given by a nonincreasing piecewise linear function $\phi_{i}$ of trip distance from $i$ to a facility. It may be reasonable to assume that for each $\phi_{i}$ there is a positive number $r_{i}$ such that $\phi_{i}(d)=0$ whenever $d>r_{i} . \phi_{i}$ is supposed to have $q_{i}$ intervals $\left[s_{1}^{i}, s_{2}^{i}\right],\left[s_{2}^{i}, s_{3}^{i}\right], \ldots,\left[s_{q_{i}}^{i},+\infty\right)$ where $s_{1}^{i}=0, s_{q_{i}}^{i}=r_{i}$, on each of which $\phi_{i}$ is linear. We can collect some of the consecutive intervals whenever $\phi_{i}$ is convex over them since our algorithm described later works as long as $\phi_{i}$ is composed of a finite number of convex pieces. Let $\left[\sigma_{1}^{i}, \sigma_{2}^{i}\right],\left[\sigma_{2}^{i}, \sigma_{3}^{i}\right], \ldots,\left[\sigma_{t_{i}}^{i},+\infty\right)$ be the resulting unified intervals. Note that $t_{i} \leq q_{i}, \sigma_{1}^{i}=0$, and $\sigma_{t_{i}}^{i} \leq r_{i}$.

We do not assume the continuity of $\phi_{i}$, but the finitely many number of points of discontinuity. Thus, $\left\{\sigma_{j}^{i} \mid j=2, \ldots, t_{i}\right\}$ includes all the discontinuous points of $\phi_{i}$. Even if $\phi_{i}$ is not continuous, the convexity of $\phi_{i}$ over each unified interval holds true (see Figure 1). ${ }^{1}$


Figure 1: Piecewise Linear Demand Function
Let $p$ be the number of facilities which the service provider can put on $T$. By the weight $w_{i}$, we mean the demand of $C_{i}$ at zero trip distance, i.e., $w_{i}=\phi_{i}(0)=\max _{d \geq 0} \phi_{i}(d)$. The service provider obtains the gain $\phi_{i}(d(i, x))$ from $i$ if and only if the facility on $x \in T$ is the nearest from $i$ among $p$ facilities. Any point on $T$ is feasible to locate facilities. The service provider's object is to maximize the total gain from the customers. Let $f(p)$ be the maximum gain which the service provider can obtain, and call it the optimal gain function

[^0]in $p^{2}$ Let $X=\left\{x_{1}, \ldots, x_{p}\right\}$ be the set of $p$ points on $T$. The multi-facility location problem can be formulated as follows:
\[

$$
\begin{equation*}
f(p)=\max _{X \text { on } T} \sum_{i \in V} \phi_{i}(d(i, X)), \tag{1}
\end{equation*}
$$

\]

where $d(i, X)=\min _{1 \leq j \leq p}\left\{d\left(i, x_{j}\right)\right\}$. On the other hand, the $p$-median problem is defined as follows:

$$
\begin{equation*}
\min _{X \text { on } T} \sum_{i \in V} w_{i} \cdot d(i, X) . \tag{2}
\end{equation*}
$$

(2) is equivalent to the following problem for any constant $L$.

$$
\max _{X \text { on } T} \sum_{i \in V}\left\{-w_{i} \cdot d(i, X)+L\right\} .
$$

If $L$ is taken to be larger than or equal to $\max _{i \in V}\left\{w_{i} \cdot r_{i}\right\},-w_{i} \cdot r_{i}+L$ is nonnegative for any $i \in V$. Moreover, $-w_{i} \cdot d(i, X)+L$ is linear and nonincreasing in trip distance $d(i, X)$. Accordingly, our multi-facility location problem is a generalization of the $p$-median problem.

Megiddo et al. [7] treat the following special case on demand function: for any $i \in V$, $q_{i}=t_{i}=2, \phi_{i}(d)=w_{i}$ if $d \in\left[0, r_{i}\right]$ and $\phi_{i}(d)=0$ if $d \in\left(r_{i},+\infty\right)$, which is convex on each of $\left[0, r_{i}\right]$ and $\left[r_{i},+\infty\right)$.

Megiddo et al. [7] show that the multi-facility location problem on a network including cycles is $\mathcal{N} \mathcal{P}$-hard in their scheme (see also Kariv and Hakimi [5]). It is a direct consequence of Megiddo et al. [7] that our model is also $\mathcal{N P}$-hard on a network including cycles (see Garey and Johnson [1]).

### 2.2. Potential locations

The facilities can be established at any point of $T$, as we stated in Section 2.1. We can, however, select in advance the potential locations to maximize the service provider's gain.

Now we construct a tree $T^{\prime}=\left(V^{\prime}, E^{\prime}\right)$ from $T=(V, E)(|V|=n,|E|=n-1)$ in the following manner. Since each $\phi_{i}$ has $t_{i}$ convex pieces, for any $e=[j, k] \in E$ the number $\tau_{e}$ of points $x^{e} \in e$ satisfying $d\left(i, x^{e}\right)=\sigma_{s}^{i}$ for some $i$ and for some $s\left(1 \leq s \leq t_{i}\right)$ does not exceed $\sum_{i=1}^{n} t_{i}$. The points $x^{e} \mathrm{~S}$ are denoted by $x_{1}^{e}, \ldots, x_{\tau_{e}}^{e}$, where the subscript is arranged so as to satisfy $d\left(j, x_{l}^{e}\right)<d\left(j, x_{l+1}^{e}\right), l=1, \ldots, \tau_{e}-1$. Let $X_{e}=\left\{x_{l}^{e} \mid l=1, \ldots, \tau_{e}\right\}$ and define the new vertex set as $V^{\prime}=V \cup\left(\bigcup_{e \in E} X_{e}\right)$. All vertices $i$ in $\bigcup_{e \in E} X_{e}$ are assumed to be $w_{i}=0$, i.e., $\phi_{i}(d)=0$, for any $d \geq 0$. Let $E_{e}^{\prime}=\left\{\left[x_{l}^{e}, x_{l+1}^{e}\right] \mid l=0, \ldots, \tau_{e}, x_{0}^{e}=j, x_{\tau_{e}+1}^{e}=k\right\}$ and define the new edge set as $E^{\prime}=\bigcup_{e \in E} E_{e}^{\prime}$. The resulting tree $T^{\prime}\left(\left|V^{\prime}\right|=n^{\prime},\left|E^{\prime}\right|=n^{\prime}-1\right)$ has $O(t(n-1))$ vertices, where $t=\sum_{i=1}^{n} t_{i}$.
Lemma 1 There exist some optimal locations $x_{1}^{*}, \ldots, x_{p}^{*} \in T^{\prime}$ such that $x_{1}^{*}, \ldots, x_{p}^{*} \in V^{\prime}$.
Proof: We redefine the demand function $\phi_{i}$ of trip distance as a demand function of a point on $T^{\prime}$. Let each $\psi_{i}(x)$ be the demand function of $i \in V^{\prime}$ on $x \in T^{\prime}$, which is also convex on any edge of $E^{\prime}$, since for any $i \in V$ and for any $[j, k] \in E^{\prime}$,

$$
d(i, j)<d(i, k) \Rightarrow\left\langle\begin{array}{l}
{[d(i, j), d(i, k)] \subset\left[\sigma_{s}^{i}, \sigma_{s+1}^{i}\right] \text { for some } s \text { or }} \\
{[d(i, j), d(i, k)] \subset\left[\sigma_{t_{i}}^{i},+\infty\right),}
\end{array}\right.
$$

[^1]and
\[

d(i, k)<d(i, j) \Rightarrow\left\langle$$
\begin{array}{l}
{[d(i, k), d(i, j)] \subset\left[\sigma_{s}^{i}, \sigma_{s+1}^{i}\right] \text { for some } s \text { or }} \\
{[d(i, k), d(i, j)] \subset\left[\sigma_{t_{i}}^{i},+\infty\right) .}
\end{array}
$$\right.
\]

The total demand on $x$ is represented by $\Psi(x)=\sum_{i \in V^{\prime}} \psi_{i}(x)$. Therefore, for any point $y=\lambda j+(1-\lambda) k, 0 \leq \lambda \leq 1$, we have

$$
\begin{aligned}
\Psi(y) & =\sum_{i \in V^{\prime}} \psi_{i}(y)=\sum_{i \in V^{\prime}} \psi_{i}(\lambda j+(1-\lambda) k) \leq \sum_{i \in V^{\prime}}\left\{\lambda \psi_{i}(j)+(1-\lambda) \psi_{i}(k)\right\} \\
& =\lambda \sum_{i \in V^{\prime}} \psi_{i}(j)+(1-\lambda) \sum_{i \in V^{\prime}} \psi_{i}(k)=\lambda \Psi(j)+(1-\lambda) \Psi(k) \\
& \leq \max \{\Psi(j), \Psi(k)\} .
\end{aligned}
$$

This implies that if $x_{i}^{*} \in[j, k]$, we can take $x_{i}^{*}$ that coincides with $j$ or $k$.
Q.E.D.

Consequently, our problem is reduced to that of finding a subset $X$ of $V^{\prime}$ in (1).
Figure 2 shows the demand on an edge between two adjacent vertices $i, j \in V$. If the service provider establishes a facility on $i \in V^{\prime}$, he obtains the gain of $w_{i}+\psi_{j}(i)$.


Figure 2: Total Demand on an Edge

### 2.3. Algorithm

The algorithm proposed here fundamentally consists of three routines $\operatorname{INT}(H, \pi, r), \operatorname{EXT}(H$, $\pi, r)$, and $\operatorname{ALLOC}^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)$, which are based on the algorithm proposed by Megiddo et al. [7]. Instead of $\operatorname{ALLOC}^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)$, they use $\operatorname{ALLOC}\left(f_{1}, \ldots, f_{k} ; \pi\right)$, where $f_{i}$ s are restricted to concave functions. By the concavity of $f_{i}$ we mean that $f_{i}(s)$ satisfies $f_{i}(s)-f_{i}(s-1) \geq f_{i}(s+1)-f_{i}(s)$ for any $s$. Recall that their model is a special case of our model. We will show through a counterexample in the next section that $f_{i}$ is not necessarily concave. This implies that their algorithm may not produce the optimal solution. On the other hand, our algorithm of ALLOC' does not require the concavity of $f_{i} \mathrm{~S}$, and generates the optimal solution.

First, we select an arbitrary vertex $u_{0} \in V^{\prime}$ as a root of $T^{\prime}$. For any pair of vertices $i, j$, let $P(i, j) \subset V^{\prime} \cup E^{\prime}$ denote the path between $i$ and $j$. For each $i \in V^{i}$ we define $V_{i}^{\prime}, E_{i}^{\prime}$ as $V_{i}^{\prime}=\left\{j \mid i \in P\left(u_{0}, j\right) \cap V^{\prime}\right\}, E_{i}^{\prime}=\left\{[a, b] \mid[a, b] \in P(i, j) \cap E^{\prime}, j \in V_{i}^{\prime}\right\}$ respectively. We call $T_{i}^{\prime}=\left(V_{i}^{\prime}, E_{i}^{\prime}\right)$ the subtree rooted at $i$. The multi-facility location problem on $T^{\prime}$ can be solved by accumulating the solutions of location problems on subtrees. Indeed, if $i \in V^{\prime}$ is a leaf, $V_{i}^{\prime}$ is a singleton and $E_{i}^{\prime}=\emptyset$. The solution of location problem on the leaf is $w_{i}$ if $p=1$ and 0 if $p=0$. Thus, if all sons of $i \in V^{\prime}$ are leaves, the location problem on $T_{i}^{\prime}$ can be solved by using the solutions given on leaves, where by the son $j$ of $i$ we mean that $j$ is adjacent to $i$ and $j \notin P\left(u_{0}, i\right)$. The iteration of the same procedure makes possible to solve the multi-facility location problem on subtree rooted at an arbitrary $i \in V^{\prime}$.

We now formally describe the algorithm. The following notations are used in the algorithm. $H$ denotes a subtree rooted at vertex $u \in V^{\prime}$, and let the sons of $u$ be $u_{1}, \ldots, u_{k}$. $H_{i}$ represents the subtree rooted at vertex $u_{i}$. Let $n_{i}$ be the number of vertices in $H_{i}$ and $d_{1}^{i} \leq \ldots \leq d_{n_{i}}^{i}$ the distances between $u_{i}$ and vertices of $H_{i}$.
$\operatorname{INT}(H, \pi, r)$ returns the maximum gain from $H$ with $\pi$ facilities under the restriction that at least one of the $\pi$ facilities is located at a distance less than or equal to $r$ from $u$. This is a routine for the problem with $\pi$ internal facilities on $H$. On the other hand, $\operatorname{EXT}(H, \pi, r)$ returns the maximum gain from $H$ with $\pi$ internal facilities when an additional facility is located outside of $H$ at a distance $r$ from $u$. This is a routine for the problem with one external facility and $\pi$ internal facilities on $H$. ALLOC ${ }^{\prime}$ is a routine to construct a solution of the problem on $H$ by using optimal solutions of subproblems $\operatorname{INT}\left(H_{i}, \pi, r\right)$ and/or $\operatorname{EXT}\left(H_{i}, \pi, r\right)(i=1, \ldots, k)$. Given the solutions $f_{1}, \ldots, f_{k}$ of the problems on $k$ subtrees, ALLOC $^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)$ returns the optimal allocation of $\pi$ facilities among subtrees to maximize the sum of $f_{i}(i=1, \ldots, k)$.

The formal descriptions of INT, EXT, and ALLOC ${ }^{\prime}$ are presented as follows:

## $\operatorname{INT}(H, \pi, r)$

case 1. [A facility is located on the root $u$ of $H$.]
Let $f_{i}\left(p_{i}\right)=\operatorname{EXT}\left(H_{i}, p_{i}, d\left(u_{i}, u\right)\right)$, for $i=1, \ldots, k$. The total gain is obtained by $w_{u}$ $+\operatorname{ALLOC}^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi-1\right)$.
case 2. [A facility is not located on the root $u$ of $H$.]
Choose a subtree $H_{j}(1 \leq j \leq k)$. For $\rho \in\left\{d_{1}^{j}, \ldots, d_{n_{j}}^{j}\right\}$ such that $\rho+d\left(u_{j}, u\right) \leq r$, let $f_{i}\left(p_{i}\right)=\operatorname{EXT}\left(H_{i}, p_{i}, \rho+d\left(u_{j}, u_{i}\right)\right)$ for $i \neq j(i=1, \ldots, k)$. Let $f_{j}\left(p_{j}\right)=\operatorname{INT}\left(H_{j}, p_{j}, \rho\right)$.
$A_{j}(\rho) \equiv \operatorname{ALLOC}^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)+\phi_{u}\left(\rho+d\left(u_{j}, u\right)\right) . A_{j}=\max _{\rho}\left\{A_{j}(\rho)\right\}$, for $j=1, \ldots, k$.
Thus, $\operatorname{INT}(H, \pi, r)$ returns a maximum value among the $A_{j} \mathrm{~s}$ in the case 2 and the value in the case 1.

## $\underline{\operatorname{EXT}(H, \pi, r)}$

case 1. [Some facility is located on $H$ within the distance $r$ from $u$.]
This is, by definition, $\operatorname{EXT}(H, \pi, r)=\operatorname{INT}(H, \pi, r)$.
case 2. [Some facility is not located on $H$ within the distance $r$ from $u$.]
In this case, there already exists a facility at the distance $r$ outside of $H$. Therefore there are no interactions between the subtrees $H_{i} \mathrm{~s}$. Thus, let $f_{i}\left(p_{i}\right)=\operatorname{EXT}\left(H_{i}, p_{i}, d\left(u_{i}\right.\right.$, $u)+r), i=1, \ldots, k$, and $A=\operatorname{ALLOC}^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)+\phi_{u}(r)$.
Thus, $\operatorname{EXT}(H, \pi, r)$ returns a maximum value among the case 1 and the case 2.
$\underline{\operatorname{ALLOC}^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)}$
Let each $f_{i}(i=1, \ldots, k)$ be monotone nondecreasing function of a nonnegative integer variable and $\pi$ be a nonnegative integer.

$$
\begin{array}{ll}
\text { Maximize } & F(\pi)=\sum_{i=1}^{k} f_{i}\left(p_{i}\right) \\
\text { subject to } & \sum_{i=1}^{k} p_{i}=\pi  \tag{3}\\
& p_{i}: \text { nonnegative integer. }
\end{array}
$$

It is known that ALLOC' can be solved by using dynamic programming. ${ }^{3}$ The total effort to solve ALLOC' is $O\left(k \pi^{2}\right)$. For more details of the algorithm, one is referred to Ibaraki and Katoh [4].

[^2]Lemma 2 The above algorithm generates an optimal solution to $\operatorname{ALLOC}{ }^{\prime}\left(f_{1}, \ldots, f_{k} ; \pi\right)$ within $O\left(k \pi^{2}\right)$ time.

We see in Section 3 how INT, EXT, and ALLOC' run by using an example.
The algorithm terminates when we obtain $f(p)=\operatorname{INT}\left(T^{\prime}, p, r^{\prime}\right)$, where $r^{\prime}$ represents the maximum value of the distances between $u_{0}$ and the vertices of $T^{\prime}$. There are $O\left(n^{\prime}\right)$ subtrees to be considered, where $n^{\prime}$ is the number of vertices in $V^{\prime}$. Each subproblem $\operatorname{INT}(H, \pi, r)$ or $\operatorname{EXT}(H, \pi, r)$ on subtree has at most $n^{\prime}$ values for the parameter $r$ and $\pi$ can take the values $0,1, \ldots, p$. Therefore, the number of different subproblems is $O\left(n^{\prime 2} p\right)$. Thus, it takes $O\left(n^{\prime 3} p^{3}\right)$ time to solve the multi-facility location problem since ALLOC' requires at most $O\left(n^{\prime} p^{2}\right)$ time. We conclude this section by the following theorem.
Theorem 1 Our algorithm computes an optimal solution to the problem (1) within a polynomial time.

## 3. An Example

We shall abbreviate the algorithm proposed by Megiddo et al. [7] to $M$-Alg.
In the model by Megiddo et al. [7], it is assumed that every customer in $C_{i}$ has a common maximum trip distance $r_{i}$ to access a facility, as we stated in Section 2.1. They state that $f_{i}$ is concave in the number of facilities. The proof, however, is not presented in Megiddo et al. [7]. Moreover, M-Alg proceeds by utilizing the concavity in ALLOC. For each $S \subset V^{\prime}$, define the gain function $W(S)=\sum_{i \in V^{\prime}} \phi_{i}(d(i, S)) .^{4} \quad$ It is known that $W(S)$ is submodular ${ }^{5}$ on the powerset of $V^{\prime}$ (see Tamir [8]). Submodularity of $W(S)$, however, doesn't necessarily imply that $f(p)$ is concave in $p$. The following example exhibits that the optimal gain function on a subtree is not concave, which implies that M-Alg may not produce an optimal solution.

## Example



Figure 3: Tree $T$

Table 1: Properties of Vertices in Tree $T$

| Vertex $(i)$ | $\mathbf{1}$ | $\mathbf{2}$ | $\mathbf{3}$ | $\mathbf{4}$ | $\mathbf{5}$ | $\mathbf{6}$ | $\mathbf{7}$ | 8 | 9 | 10 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Maximum trip distance $\left(r_{i}\right)$ | 1 | 2 | 1 | 6 | 6 | 6 | 1 | 6 | 6 | 6 |
| Weight $\left(w_{i}\right)$ | 0 | 1 | 4 | 3 | 3 | 3 | 1 | 3 | 3 | 3 |

[^3]Consider a tree $T$ described by Figure 3 and Table 1, where the length of each edge is assumed to be 5 . For any vertex $i, \phi_{i}(d)=w_{i}$ if $d \in\left[0, r_{i}\right]$ and $\phi_{i}(d)=0$ if $d \in\left(r_{i},+\infty\right)$. A service provider is to establish 3 facilities on $T$.

Now, let $U_{i}$ be the $r_{i}$-neighborhood of $i \in V$, i.e., $U_{i}=\left\{x \mid d(i, x) \leq r_{i}\right\}$. For every set $S \subset V$, let $U_{S}=\cap_{i \in S} U_{i}$. $S$ is said to be maximal, if $U_{S} \neq \emptyset$ and $U_{R}=\emptyset$ for every $R \supset S$ and $R \neq S$. Without loss of generality, we may assume that every facility belongs to $U_{S}$ for some maximal $S$. For every maximal $S$ each $x \in U_{S}$ brings the same gain to the service provider. Thus, for each maximal $S$, we can select a representative point $y_{S} \in U_{S}$ as a facility location in the following manner: If $U_{S}$ includes some vertices, let $y_{S}=i \in U_{S} \cap V$. Otherwise, choose any $y_{S} \in U_{S}$ and regard it as a new vertex possessing no customer and having zero weight, i.e., $w_{y_{5}}=0$. The maximal sets are $S_{1}=\{\mathbf{1}\}, S_{2}=\{\mathbf{2}, 4,5,6\}, S_{3}=\{\mathbf{3}\}, S_{4}=\{\mathbf{4}, 8\}$, $S_{5}=\{\mathbf{5}, 9\}, S_{6}=\{\mathbf{6}, 10\}$, and $S_{7}=\{\mathbf{7}\}$. Since $i \in U_{S_{i}} \cap V, i=1, \ldots, 7$, we can select each $i(1 \leq i \leq 7)$ as the facility location of $S_{i}$.

The optimal gain $f(p)$ is obtained by $\operatorname{INT}\left(T, p, r^{\prime}\right)$, where $T$ is rooted at vertex $1, p=3$, and $r^{\prime}=15$. There are no interactions among vertex 1 , subtree $T_{2}$, and $T_{3}$, where $T_{2}$ and $T_{3}$ represent the subtrees rooted at vertices 2,3 respectively. Moreover, locating a facility at vertex 1 doesn't make sense because the service provider gains nothing. It implies that it is sufficient to consider the case 2 of routine $\operatorname{INT}\left(T, p, r^{\prime}\right)$ to solve this example. The case 2 first requires $\operatorname{INT}\left(T_{2}, s, \rho_{1}\right)$ and $\operatorname{EXT}\left(T_{3}, s, \rho_{1}+10\right)$ for $s=0,1, \ldots, p$ and each $\rho_{1} \in\{0,5,10\}$, and secondly $\operatorname{EXT}\left(T_{2}, s, \rho_{2}+10\right)$ and $\operatorname{INT}\left(T_{3}, s, \rho_{2}\right)$ for $s=0,1, \ldots, p$ and each $\rho_{2} \in\{0,5\}$. Thus, if we run M-Alg, the algorithm solves $\operatorname{ALLOC}\left(f_{1}, f_{2} ; 3\right)$ at the final step, where $f_{1}(s)$ and $f_{2}(s)$ are the optimal gains on $T_{2}$ and $T_{3}$ as follows:

Table 2: Optimal Gains on $T_{2}$

| $s$ | $f_{1}(s)$ | Location points | Covered maximal sets | $f_{1}(s)-f_{1}(s-1)$ |
| :---: | :---: | :--- | :--- | :---: |
| 1 | 10 | 2 | $S_{2}$ | 10 |
| 2 | 13 | 2,4 | $S_{2}, S_{4}$ | 3 |
| 3 | 18 | $4,5,6$ | $S_{4}, S_{5}, S_{6}$ | 5 |

Table 3: Optimal Gains on $T_{3}$

| $s$ | $f_{2}(s)$ | Location points | Covered maximal sets | $f_{2}(s)-f_{2}(s-1)$ |
| :---: | :---: | :--- | :--- | :---: |
| 1 | 4 | 3 | $S_{3}$ | 4 |
| 2 | 5 | 3,7 | $S_{3}, S_{7}$ | 1 |

Since $f_{1}(2)-f_{1}(1)=3<f_{1}(3)-f_{1}(2)=5$, the optimal gain function $f_{1}$ is not concave. Thus, ALLOC is not applicable to this example.

If we apply ALLOC ${ }^{\prime}$, the function $F$ is constructed from $f_{1}(s)$ and $f_{2}(s)$ as follows: $F(0)=0, F(1)=\max _{0 \leq l \leq 1}\left\{f_{1}(1-l)+f_{2}(l)\right\}=f_{1}(1)+f_{2}(0)=10, F(2)=\max _{0 \leq l \leq 2}\left\{f_{1}(2-\right.$ $\left.l)+f_{2}(l)\right\}=f_{1}(1)+f_{2}(1)=14, F(3)=\max _{0 \leq l \leq 3}\left\{f_{1}(3-l)+f_{2}(l)\right\}=f_{1}(3)+f_{2}(0)=18$. Thus, we have $\operatorname{INT}(T, 3,15)=F(3)=18$. This is the optimal solution to this example, that locates facilities at vertices 4,5 , and 6 .

## 4. Concluding Remarks

In this section, we explore some possible extensions of this paper as concluding remarks.

This paper describes the multi-facility location problem assuming that there is no existing facility. In practice, one may have to consider the problem of locating new facilities in addition to existing ones. This problem can be easily accommodated by setting demand function $\phi_{i}(d)$ to be zero for $d$ larger than the distance between $i$ and the nearest existing facility.

Implicitly assumed in this paper is the uniformity of price. In some cases, it may be reasonable to consider that the commodity price at each facility is a control variable. This will bring another dimension to the optimization problem.

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Masashi Umezawa<br>Department of Administration Engineering Faculty of Science and Technology<br>Keio University<br>Kohoku-ku, Yokohama 223-8522, Japan<br>E-mail: ume@ae.keio.ac.jp


[^0]:    ${ }^{1}$ Every nonincreasing function with a finite support can be approximated by a piecewise linear function at an arbitrary given level of accuracy. Thus, even if $\phi_{i}$ is not piecewise linear, our scheme is applicable to an approximated problem.

[^1]:    ${ }^{2}$ It is easy to see that $f$ is monotone nondecreasing. Indeed, for $1 \leq s \leq p, f(s)=f(s+1)$ if $f(s)=$ $\sum_{j \in V} w_{j}$, and $f(s)<f(s+1)$ otherwise since $f(s)<\sum_{j \in V} w_{j}$ implies the existence of an uncovered $j^{*} \in V$.

[^2]:    ${ }^{3}$ Use $F(s):=\max _{0 \leq l \leq s}\left\{F(s-l)+f_{i}(l)\right\}, s=1, \ldots \pi$ recursively for $i=1, \ldots, k$.

[^3]:    ${ }^{4}$ When $S=X$, we can rewrite (1) as follows: $f(p)=\max _{X o n T} W(X)$.
    ${ }^{5} W(S)$ is said to be submodular on the powerset of $V^{\prime}$ if for any $S \subset R \subset V^{\prime}, R \neq V^{\prime}$, and any $i \notin R$, $W(S \cup\{i\})-W(S) \geq W(R \cup\{i\})-W(R)$ holds.

