

ON THE CONVERGENCE OF A HYPERBOLOID APPROXIMATION PROCEDURE FOR A PERTURBED GENERALIZED EUCLIDEAN MULTIFACILITY LOCATION PROBLEM

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For a perturbed generalized multifacility location problem, we prove that a hyperboloid approximation procedure is convergent under certain conditions.

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1. INTRODUCTION

Let a_1, a_2, \dots, a_m be m points in \mathbf{R}^d , the d -dimensional Euclidean space. Let w_{ji} , $j = 1, 2, \dots, n$, $i = 1, 2, \dots, m$, and v_{jk} , $1 \leq j < k \leq n$ be given nonnegative numbers. For convenience, we assume $v_{jk} = v_{kj}$ whenever $j > k$ and $v_{jj} = 0$ for all j . Also, all vectors are assumed to be column vectors in this paper. Let B_{ji} , $j = 1, 2, \dots, n$, $i = 1, 2, \dots, m$, and D_{jk} , $1 \leq j < k \leq n$ be given symmetric positive definite square d -matrices. For convenience, we assume $D_{jk} = D_{kj}$ whenever $j > k$. Preda and Niculescu [5] defined the generalized Euclidean multifacility location (GEMFL) problem, which is to find a point $x = (x_1^T, x_2^T, \dots, x_n^T)^T \in \mathbf{R}^{n \times d}$ that will minimize

$$f(x) = \sum_{j=1}^n \sum_{i=1}^m w_{ji} \sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i)} + \sum_{1 \leq j < k \leq n} v_{jk} \sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k)},$$

where T means transpose. When $B_{ji} = I$, $j = 1, 2, \dots, n$, $i = 1, 2, \dots, m$, and $D_{jk} = I$, $1 \leq j < k \leq n$, where I is the unit square d -matrix, is obtained the Euclidean multifacility location (EMFL) problem.

In this problem, a_1, a_2, \dots, a_m represent the location of m existing facilities; x_1, x_2, \dots, x_n represent the locations of n new facilities.

To avoid nondifferentiability, following the idea of Eyster, White and Wierwille [1], Preda and Niculescu [5] introduced a small positive number ε to the original problem, getting the following smooth perturbed objective

function

$$(1) \quad f_\varepsilon(x) = \sum_{j=1}^n \sum_{i=1}^m w_{ji} \sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon} \\ + \sum_{1 \leq j < k \leq n} v_{jk} \sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}.$$

A minimum point of $f_\varepsilon(x)$ is called an ε -optimal solution to the GEMFL problem.

In this paper, we continue the work of Preda and Niculescu [5], further generalizing results obtained by Rosen and Xue [10] for the perturbed EMFL problem. On the line of papers Preda et al. [6], Preda and Batatorescu [7], Preda and Chitescu [8] and Preda [9] we can formulate some problems of this type.

The gradient of f_ε with respect to the j th new facility x_j is

$$(2) \quad \nabla_j f_\varepsilon(x) = \sum_{i=1}^m w_{ji} \frac{B_{ji}(x_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} \\ + \sum_{k \neq j} v_{jk} \frac{D_{jk}(x_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}}.$$

As in Weiszfeld [11] and Miehle [3], we may get an improved location x_j^\dagger of the j th new facility with respect to the existing facilities and the other new facilities by solving the system of linear equations

$$(3) \quad \sum_{i=1}^m w_{ji} \frac{B_{ji}(x_j^\dagger - a_i)}{\sqrt{(x_j^\dagger - a_i)^T B_{ji} (x_j^\dagger - a_i) + \varepsilon}} + \sum_{k \neq j} v_{jk} \frac{D_{jk}(x_j^\dagger - x_k)}{\sqrt{(x_j^\dagger - x_k)^T D_{jk} (x_j^\dagger - x_k) + \varepsilon}} = 0$$

for x_j^\dagger . This gives

$$(4) \quad x_j^\dagger = T_j(x_1, x_2, \dots, x_n),$$

where $T_j : \mathbf{R}^{n \times d} \rightarrow \mathbf{R}^d$, $j = 1, 2, \dots, n$, is defined by

$$(5) \quad T_j(x_1, x_2, \dots, x_n) \\ = \left[\sum_{i=1}^m \frac{w_{ji} B_{ji}}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} \frac{v_{jk} D_{jk}}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}} \right]^{-1} \\ = \left[\sum_{i=1}^m w_{ji} \frac{B_{ji} a_i}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} v_{jk} \frac{D_{jk} x_k}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}} \right].$$

2. THE HYPERBOLOID APPROXIMATION PROCEDURE AND SOME PRELIMINARY RESULTS

Algorithm HAP

Step_0. Choose any initial point $x^0 \in \mathbf{R}^{n \times d}$. Set $s = 0$ and go to Step_1.

Step_1. For $j := 1, 2, \dots, n$ do $x_j^{s+1} = T_j(x_1^s, x_2^s, \dots, x_n^s)$.

Step_2. If $x^{s+1} = x^s$, stop; otherwise, replace s with $s + 1$ and go to Step_1.

Let x^0 be given by

$$x_j^0 = \begin{cases} \left(\sum_{i=1}^m w_{ji} B_{ji} \right)^{-1} \left(\sum_{i=1}^m w_{ji} B_{ji} a_i \right) & \text{if } \sum_{i=1}^m w_{ji} > 0 \\ \frac{\sum_{i=1}^m B_{ji} a_i}{m} & \text{otherwise} \end{cases} \quad j = 1, 2, \dots, n.$$

A new facility x_j and an existing facility a_i are said to have an *exchange* whenever $w_{ji} > 0$. Two new facilities x_j and x_k are said to have an *exchange* whenever $v_{jk} > 0$. A new facility x_{j_0} is said to be *chained* if there exist $j_1, j_2, \dots, j_l \in \{1, 2, \dots, n\}$ and $i_0 \in \{1, 2, \dots, m\}$ such that $v_{j_0 j_1} \dots v_{j_{l-1} j_l} w_{j_l i_0} \neq 0$. A variable x_j which is not chained is called a *free* variable. Let F and C be the index sets for free variables and chained variables, respectively. We can rewrite $f_\varepsilon(x)$ as

$$(6) \quad \begin{aligned} f_\varepsilon(x) &= \sum_{j \in C} \sum_{i=1}^m w_{ji} \sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon} \\ &+ \sum_{\substack{j, k \in C \\ 1 \leq j < k \leq n}} v_{jk} \sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon} \\ &+ \sum_{\substack{j, k \in F \\ 1 \leq j < k \leq n}} v_{jk} \sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}. \end{aligned}$$

With no loss of generality [6], we assume in the rest of this paper that there is no free variable in the GEMFL problem or, in terms of Francis and Cabot [2] that the problem is *fully chained*.

With this assumption, $f_\varepsilon(x)$ is a strictly convex function for $\varepsilon > 0$ and has arbitrarily high derivatives.

PROPOSITION 1. $\lim_{\|x\| \rightarrow \infty} f_\varepsilon(x) = +\infty$. Therefore, the GEMFL problem has a unique ε -optimal solution for each $\varepsilon > 0$.

Proof. If $\|x\| \rightarrow \infty$, then $\|x_{j_0}\| \rightarrow \infty$ for some $j_0 \in \{1, 2, \dots, n\}$. Since GEMFL is fully chained, there exist $j_1, j_2, \dots, j_l \in \{1, 2, \dots, n\}$, $i_0 \in$

$\{1, 2, \dots, m\}$ such that $v_{j_0 j_1} \dots v_{j_{l-1} j_l} w_{j_l i_0} \neq 0$. As a consequence, we have

$$(7) \quad \lim_{\|x\| \rightarrow \infty} \left[\sum_{0 \leq k < l} v_{j_k j_{k+1}} \sqrt{(x_{j_k} - x_{j_{k+1}})^T D_{j_k j_{k+1}} (x_{j_k} - x_{j_{k+1}}) + \varepsilon} \right. \\ \left. + w_{j_l i_0} \sqrt{(x_{j_l} - a_{i_0})^T B_{j_l i_0} (x_{j_l} - a_{i_0}) + \varepsilon} \right] = +\infty.$$

Therefore, $\lim_{\|x\| \rightarrow \infty} f_\varepsilon(x) = +\infty$. This, together with the continuity of $f_\varepsilon(x)$, guarantees the existence of a minimizer of $f_\varepsilon(x)$. Since $f_\varepsilon(x)$ is strictly convex, the minimizer is unique. \square

PROPOSITION 2. *If $B_{j_i} = \alpha_{j_i} B_j$, for any $i \in \{1, 2, \dots, m\}$, $j \in \{1, 2, \dots, n\}$, and $D_{j_k} = \beta_{j_k} B_j$, for any $j, k \in \{1, 2, \dots, n\}$, $j \neq k$, where $\alpha_{j_i} > 0$, for any $i \in \{1, 2, \dots, m\}$, $j \in \{1, 2, \dots, n\}$, $\beta_{j_k} > 0$, for any $j, k \in \{1, 2, \dots, n\}$, $j \neq k$, and B_j is symmetric and positive definite, for any $j \in \{1, 2, \dots, n\}$, then for any $j \in \{1, 2, \dots, n\}$, $T_j(x_1, x_2, \dots, x_n)$ is in the convex hull of the points a_1, a_2, \dots, a_m and x_1, x_2, \dots, x_n .*

Proof. It follows from (5) that

$$\begin{aligned} & T_j(x_1, x_2, \dots, x_n) \\ &= \left[\sum_{i=1}^m \frac{w_{j_i} \alpha_{j_i} B_j}{\sqrt{\alpha_{j_i} (x_j - a_i)^T B_j (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} \frac{v_{j_k} \beta_{j_k} B_j}{\sqrt{\beta_{j_k} (x_j - x_k)^T B_j (x_j - x_k) + \varepsilon}} \right]^{-1} \\ & \left[\sum_{i=1}^m w_{j_i} \frac{\alpha_{j_i} B_j a_i}{\sqrt{\alpha_{j_i} (x_j - a_i)^T B_j (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} v_{j_k} \frac{\beta_{j_k} B_j x_k}{\sqrt{\beta_{j_k} (x_j - x_k)^T B_j (x_j - x_k) + \varepsilon}} \right] \\ &= \left[\sum_{i=1}^m \frac{w_{j_i} \alpha_{j_i}}{\sqrt{\alpha_{j_i} (x_j - a_i)^T B_j (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} \frac{v_{j_k} \beta_{j_k}}{\sqrt{\beta_{j_k} (x_j - x_k)^T B_j (x_j - x_k) + \varepsilon}} \right]^{-1} \\ & B_j^{-1} \left[\sum_{i=1}^m w_{j_i} \frac{\alpha_{j_i} B_j a_i}{\sqrt{\alpha_{j_i} (x_j - a_i)^T B_j (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} v_{j_k} \frac{\beta_{j_k} B_j x_k}{\sqrt{\beta_{j_k} (x_j - x_k)^T B_j (x_j - x_k) + \varepsilon}} \right] \\ &= \left[\sum_{i=1}^m \frac{w_{j_i} \alpha_{j_i}}{\sqrt{\alpha_{j_i} (x_j - a_i)^T B_j (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} \frac{v_{j_k} \beta_{j_k}}{\sqrt{\beta_{j_k} (x_j - x_k)^T B_j (x_j - x_k) + \varepsilon}} \right]^{-1} \\ &= \left[\sum_{i=1}^m w_{j_i} \frac{\alpha_{j_i} a_i}{\sqrt{\alpha_{j_i} (x_j - a_i)^T B_j (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} v_{j_k} \frac{\beta_{j_k} x_k}{\sqrt{\beta_{j_k} (x_j - x_k)^T B_j (x_j - x_k) + \varepsilon}} \right], \end{aligned}$$

and this is a convex combination of the points a_1, a_2, \dots, a_m and x_1, x_2, \dots, x_n . \square

THEOREM 1. *Let $x = (x_1, x_2, \dots, x_n)$ be any point in $\mathbf{R}^{n \times d}$. Let $y = (y_1, \dots, y_n)$ be the point generated by*

$$(8) \quad y_j = T_j(x_1, x_2, \dots, x_n), \quad j = 1, 2, \dots, n.$$

*Then the following descent property for the **HAP** holds as long as $\varepsilon > 0$.*

$$(9) \quad 2f_\varepsilon(x) - 2f_\varepsilon(y) \geq \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{\mathcal{A}}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} \\ + \sum_{j=1}^n \sum_{k>j} v_{jk} \frac{\left[\sqrt{(y_j - y_k)^T D_{jk}(y_j - y_k) + \varepsilon} - \sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon} \right]^2}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}},$$

where

$$\mathcal{A} = \left[\sqrt{(y_j - a_i)^T B_{ji}(y_j - a_i) + \varepsilon} - \sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon} \right]^2 \\ + (y_j - x_j)^T B_{ji}(y_j - x_j).$$

Proof. Since $y_j = T_j(x_1, x_2, \dots, x_n)$, it follows from (3) that

$$(10) \quad \sum_{i=1}^m w_{ji} \frac{B_{ji}(y_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} \\ + \sum_{k \neq j} v_{jk} \frac{D_{jk}(y_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}} = 0.$$

Multiplying both sides of (10) by $(y_j - x_j)^T$ and rearranging terms, we get

$$(11) \quad \sum_{i=1}^m w_{ji} \frac{(y_j - a_i)^T B_{ji}(y_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} \\ + \sum_{k \neq j} v_{jk} \frac{(y_j - x_k)^T D_{jk}(y_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}} - (y_j - x_j)^T \nabla_j f_\varepsilon(x) \\ = \sum_{i=1}^m w_{ji} \frac{(x_j - a_i)^T B_{ji}(x_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} + \sum_{k \neq j} v_{jk} \frac{(x_j - x_k)^T D_{jk}(x_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}}.$$

By definition,

$$(12) \quad y_j = x_j - \left[\sum_{i=1}^m w_{ji} \frac{B_{ji}}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} \right. \\ \left. + \sum_{k \neq j} v_{jk} \frac{D_{jk}}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}} \right]^{-1} \nabla_j f_\varepsilon(x).$$

Therefore,

$$(13) \quad -(y_j - x_j)^T \nabla_j f_\varepsilon(x) = (y_j - x_j)^T \left[\sum_{i=1}^m w_{ji} \frac{B_{ji}}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} + \sum_{k \neq j} v_{jk} \frac{D_{jk}}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}} \right] (y_j - x_j).$$

Combining (11) and (13), we get

$$(14) \quad \begin{aligned} & \sum_{i=1}^m w_{ji} \frac{(y_j - a_i)^T B_{ji} (y_j - a_i) + (y_j - x_j)^T B_{ji} (y_j - x_j)}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} \\ & + \sum_{k \neq j} v_{jk} \frac{(y_j - x_k)^T D_{jk} (y_j - x_k) + (y_j - x_j)^T D_{jk} (y_j - x_j) - \frac{1}{2} (x_j - x_k)^T D_{jk} (x_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}} \\ & = \sum_{i=1}^m w_{ji} \frac{(x_j - a_i)^T B_{ji} (x_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} + \frac{1}{2} \sum_{k \neq j} v_{jk} \frac{(x_j - x_k)^T D_{jk} (x_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}}. \end{aligned}$$

Summing (14) over j (note that (14) is true for all j), since $D_{jk} = D_{kj}$, $\forall j \neq k$, we get

$$(15) \quad \begin{aligned} & \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{(y_j - a_i)^T B_{ji} (y_j - a_i) + (y_j - x_j)^T B_{ji} (y_j - x_j)}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} \\ & + \sum_{j=1}^n \sum_{k > j} v_{jk} \frac{\mathcal{B}}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}} = \\ & = \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{(x_j - a_i)^T B_{ji} (x_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} + \sum_{j=1}^n \sum_{k > j} v_{jk} \frac{(x_j - x_k)^T D_{jk} (x_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}}, \end{aligned}$$

where $\mathcal{B} = (y_j - x_k)^T D_{jk} (y_j - x_k) + (y_k - x_j)^T D_{jk} (y_k - x_j) + (y_j - x_j)^T D_{jk} (y_j - x_j) + (y_k - x_k)^T D_{jk} (y_k - x_k) - (x_j - x_k)^T D_{jk} (x_j - x_k)$.

Since D_{jk} is symmetrical and positive definite, we have $(y_j - x_k)^T D_{jk} (y_j - x_k) + (y_k - x_j)^T D_{jk} (y_k - x_j) + (y_j - x_j)^T D_{jk} (y_j - x_j) + (y_k - x_k)^T D_{jk} (y_k - x_k) - (x_j - x_k)^T D_{jk} (x_j - x_k) - (y_j - y_k)^T D_{jk} (y_j - y_k) = (y_j - x_k + y_k - x_j)^T D_{jk} (y_j - x_k + y_k - x_j) \geq 0$. Therefore, we get

$$(16) \quad \begin{aligned} & (y_j - x_k)^T D_{jk} (y_j - x_k) + (y_k - x_j)^T D_{jk} (y_k - x_j) \\ & + (y_j - x_j)^T D_{jk} (y_j - x_j) + (y_k - x_k)^T D_{jk} (y_k - x_k) \\ & \geq (x_j - x_k)^T D_{jk} (x_j - x_k) + (y_j - y_k)^T D_{jk} (y_j - y_k). \end{aligned}$$

Combining (15) and (16), we get

$$(17) \quad \begin{aligned} & \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{(y_j - a_i)^T B_{ji}(y_j - a_i) + (y_j - x_j)^T B_{ji}(y_j - x_j)}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} \\ & \quad + \sum_{j=1}^n \sum_{k>j} v_{jk} \frac{(y_j - y_k)^T D_{jk}(y_j - y_k)}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}} \\ & \leq \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{(x_j - a_i)^T B_{ji}(x_j - a_i)}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} + \sum_{j=1}^n \sum_{k>j} v_{jk} \frac{(x_j - x_k)^T D_{jk}(x_j - x_k)}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}}. \end{aligned}$$

Adding $\sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{\varepsilon}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} + \sum_{j=1}^n \sum_{k>j} v_{jk} \frac{\varepsilon}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}}$ to both sides of (17), we get

$$(18) \quad \begin{aligned} & \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{(y_j - a_i)^T B_{ji}(y_j - a_i) + \varepsilon + (y_j - x_j)^T B_{ji}(y_j - x_j)}{\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon}} \\ & \quad + \sum_{j=1}^n \sum_{k>j} v_{jk} \frac{(y_j - y_k)^T D_{jk}(y_j - y_k) + \varepsilon}{\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon}} \leq f_\varepsilon(x). \end{aligned}$$

Following the ideas of Ostresh [4] and Weiszfeld [11], we have

$$(19) \quad \begin{aligned} & (y_j - a_i)^T B_{ji}(y_j - a_i) + \varepsilon \\ & = \left[\sqrt{(y_j - a_i)^T B_{ji}(y_j - a_i) + \varepsilon} - \sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon} \right]^2 \\ & \quad + \left[\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon} \right]^2 + 2\sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon} \\ & \quad \cdot \left[\sqrt{(y_j - a_i)^T B_{ji}(y_j - a_i) + \varepsilon} - \sqrt{(x_j - a_i)^T B_{ji}(x_j - a_i) + \varepsilon} \right]. \end{aligned}$$

Also,

$$(20) \quad \begin{aligned} & (y_j - y_k)^T D_{jk}(y_j - y_k) + \varepsilon \\ & = \left[\sqrt{(y_j - y_k)^T D_{jk}(y_j - y_k) + \varepsilon} - \sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon} \right]^2 \\ & \quad + \left[\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon} \right]^2 + 2\sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon} \\ & \quad \cdot \left[\sqrt{(y_j - y_k)^T D_{jk}(y_j - y_k) + \varepsilon} - \sqrt{(x_j - x_k)^T D_{jk}(x_j - x_k) + \varepsilon} \right]. \end{aligned}$$

Substituting (19) and (20) into (18), we get

$$(21) \quad \sum_{j=1}^n \sum_{i=1}^m w_{ji} \frac{\mathcal{C}}{\sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon}} \\ + \sum_{j=1}^n \sum_{k>j} v_{jk} \frac{\left[\sqrt{(y_j - y_k)^T D_{jk} (y_j - y_k) + \varepsilon} - \sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon} \right]^2}{\sqrt{(x_j - x_k)^T D_{jk} (x_j - x_k) + \varepsilon}} \\ + 2f_\varepsilon(y) - f_\varepsilon(x) \leq f_\varepsilon(x),$$

where

$$\mathcal{C} = \left[\sqrt{(y_j - a_i)^T B_{ji} (y_j - a_i) + \varepsilon} - \sqrt{(x_j - a_i)^T B_{ji} (x_j - a_i) + \varepsilon} \right]^2 \\ + (y_j - x_j)^T B_{ji} (y_j - x_j).$$

This is equivalent to (9). \square

3. THE CONVERGENCE THEOREM AND SOME COROLLARIES

We assume throughout this section that $y = (y_1, \dots, y_n) = (T(x_1), \dots, T(x_n))$.

LEMMA 1. *If there exist $j_0 \in \{1, 2, \dots, n\}$ and $i_0 \in \{1, 2, \dots, m\}$ such that*

$$(22) \quad w_{j_0 i_0} > 0, \quad \nabla_{j_0} f_\varepsilon(x) \neq 0,$$

then

$$f_\varepsilon(y) \leq f_\varepsilon(x) - \frac{w_{j_0 i_0}}{2\sqrt{(x_{j_0} - a_{i_0})^T B_{j_0 i_0} (x_{j_0} - a_{i_0}) + \varepsilon}} (y_{j_0} - x_{j_0})^T \\ \cdot B_{j_0 i_0} (y_{j_0} - x_{j_0}) < f_\varepsilon(x).$$

Proof. From Theorem 1 we have

$$f_\varepsilon(y) \leq f_\varepsilon(x) - \frac{w_{j_0 i_0}}{2\sqrt{(x_{j_0} - a_{i_0})^T B_{j_0 i_0} (x_{j_0} - a_{i_0}) + \varepsilon}} (y_{j_0} - x_{j_0})^T B_{j_0 i_0} (y_{j_0} - x_{j_0}).$$

Combining (12) with (22) we get

$$(23) \quad \frac{w_{j_0 i_0}}{2\sqrt{(x_{j_0} - a_{i_0})^T B_{j_0 i_0} (x_{j_0} - a_{i_0}) + \varepsilon}} (y_{j_0} - x_{j_0})^T B_{j_0 i_0} (y_{j_0} - x_{j_0}) > 0.$$

This completes the proof. \square

LEMMA 2. *If there exist $j_0, k_0 \in \{1, 2, \dots, n\}$ such that $v_{j_0 k_0} > 0$, $\nabla_{j_0} f_\varepsilon(x) \neq 0$ and $\nabla_{k_0} f_\varepsilon(x) = 0$, then*

$$\begin{aligned} f_\varepsilon(y) &\leq f_\varepsilon(x) - \frac{v_{j_0 k_0}}{2\sqrt{(x_{j_0} - x_{k_0})^T B_{j_0 k_0} (x_{j_0} - x_{k_0})} + \varepsilon} (y_{j_0} - x_{j_0})^T B_{j_0 k_0} (y_{j_0} - x_{j_0}) \\ &< f_\varepsilon(x). \end{aligned}$$

Proof. It follows from $\nabla_{k_0} f_\varepsilon(x) = 0$ and (12) that $y_{k_0} = x_{k_0}$. If we fix x_{k_0} at its current value, treat x_{k_0} as an extra existing facility instead of a new facility, and treat $v_{j k_0}$ as the weight on the generalized distance from the j th new facility to this extra existing facility for $j \neq k_0$, then we can consider the current GEMFL problem as a new GEMFL problem with $m + 1$ existing facilities and $n - 1$ new facilities. Taking one step of the HAP algorithm on this new problem will result in exactly the same values for the j th new facility for all $j \neq k_0$. Applying Lemma 1 to this new GEMFL problem, we get the desired inequality. \square

THEOREM 2. *If $\nabla f_\varepsilon(x) \neq 0$, then $f_\varepsilon(y) < f_\varepsilon(x)$.*

Proof. Since $\nabla f_\varepsilon(x) \neq 0$, there exists $j_0 \in \{1, 2, \dots, n\}$ such that $\nabla_{j_0} f_\varepsilon(x) \neq 0$. Since variable x_{j_0} is chained, there exist $j_1, j_2, \dots, j_l \in \{1, 2, \dots, n\}$ and $i_0 \in \{1, 2, \dots, m\}$ such that $v_{j_0 j_1} \dots v_{j_{l-1} j_l} w_{j_l i_0} > 0$.

Let $r = \max\{i \mid \nabla_{j_i} f_\varepsilon(x) \neq 0, 0 \leq i \leq l\}$. If $r = l$, it follows from Lemma 1 that $f_\varepsilon(y) < f_\varepsilon(x)$. If $r < l$, it follows from Lemma 2 that $f_\varepsilon(y) < f_\varepsilon(x)$. \square

THEOREM 3. *From any initial point $x^0 \in \mathbf{R}^{n \times d}$, the HAP either stops at the ε -optimal solution of GEMFL, or generates an infinite sequence $\{x^s\}$. If $\{x^s\}$ is bounded, then $\{x^s\}$ converges to the ε -optimal solution of GEMFL.*

Proof. If the HAP stops at some iteration, then $x^{s+1} = x^s$ for some integer s . It follows from the definition of the algorithm that $\nabla_j f_\varepsilon(x^s) = 0$, $j = 1, 2, \dots, n$. Therefore, $\nabla f_\varepsilon(x) = 0$ and x^s is the ε -optimal solution of GEMFL.

Now suppose that HAP generates an infinite sequence $\{x^s\}$, which is bounded. Suppose that $\{x^s\}$ does not converge to the ε -optimal solution of GEMFL, there would exist a subsequence $\{x^{r_s}\}$ that converges to a point \bar{x} , which is not the ε -optimal solution of GEMFL. Without loss of generality, we may assume that the subsequent $\{x^{r_s+1}\}$ converges to some point \hat{x} .

From the continuity, we have

$$(24) \quad \lim_{r_s \rightarrow \infty} f_\varepsilon(x^{r_s}) = f_\varepsilon(\bar{x}), \quad \lim_{r_s \rightarrow \infty} f_\varepsilon(x^{r_s+1}) = f_\varepsilon(\hat{x}).$$

Since $\{f_\varepsilon(x^s)\}$ is monotonically decreasing, (24) implies

$$(25) \quad f_\varepsilon(\bar{x}) = \lim_{r_s \rightarrow \infty} f_\varepsilon(x^{r_s}) = \lim_{r_s \rightarrow \infty} f_\varepsilon(x^{r_s+1}) = f_\varepsilon(\hat{x}).$$

It follows from the continuity of $T(x)$ that

$$(26) \quad \widehat{x} = \lim_{r_s \rightarrow \infty} x^{r_s+1} = \lim_{r_s \rightarrow \infty} T(x^{r_s}) = T(\bar{x}).$$

It follows from Theorem 2 that

$$(27) \quad f_\varepsilon(\widehat{x}) < f_\varepsilon(\bar{x}).$$

This is in contradiction with (25) and the proof is complete. \square

COROLLARY 1. *If $B_{ji} = \alpha_{ji}B_j$, for any $i \in \{1, 2, \dots, m\}$, $j \in \{1, 2, \dots, n\}$, and $D_{jk} = \beta_{jk}B_j$, for any $j, k \in \{1, 2, \dots, n\}$, $j \neq k$, where $\alpha_{ji} > 0$, for any $i \in \{1, 2, \dots, m\}$, $j \in \{1, 2, \dots, n\}$, $\beta_{jk} > 0$, for any $j, k \in \{1, 2, \dots, n\}$, $j \neq k$, and B_j is symmetric and positive definite, for any $j \in \{1, 2, \dots, n\}$, then from any initial point $x^0 \in \mathbf{R}^{n \times d}$, the HAP either stops at the ε -optimal solution of GEMFL, or generates an infinite sequence $\{x^s\}$ converging to the ε -optimal solution of GEMFL.*

Proof. From Proposition 2 it follows that if HAP generates an infinite sequence $\{x^s\}$, then $\{x^s\}$ is bounded. We apply now Theorem 3. \square

COROLLARY 2. *If $B_{ji} = \alpha_{ji}B_j$, for any $i \in \{1, 2, \dots, m\}$, $j \in \{1, 2, \dots, n\}$, and $D_{jk} = \beta_{jk}B_j$, for any $j, k \in \{1, 2, \dots, n\}$, $j \neq k$, where $\alpha_{ji} > 0$, for any $i \in \{1, 2, \dots, m\}$, $j \in \{1, 2, \dots, n\}$, $\beta_{jk} > 0$, for any $j, k \in \{1, 2, \dots, n\}$, $j \neq k$, and B_j is symmetric and positive definite, for any $j \in \{1, 2, \dots, n\}$, then the unique ε -optimal solution of GEMFL problem is in the convex hull of the existing facilities.*

Proof. Start the HAP with any point in the convex hull of the existing facilities as the initial point. From Proposition 2, the sequence $\{x^s\}$ is in the convex hull of the existing facilities. From Corollary 1, the unique ε -optimal solution for the GEMFL problem either is one of this points or the limit of this sequence. Therefore, it is in the convex hull of the existing facilities. \square

A future direction of research is to look for other conditions on the matrices B_{ji} and D_{jk} , in order to assure the boundedness of the sequence $\{x^s\}$.

REFERENCES

- [1] J.W. Eyster, J.A. White and W.W. Wierwille, *On Solving Multifacility Location Problems Using a Hyperboloid Approximation Procedure*. AIIE Trans. **5** (1973), 1–6.
- [2] R.L. Francis and A.V. Cabot, *Properties of a Multifacility Location Problem Involving Euclidean Distances*. Naval Res. Logist. Quart. **19** (1972), 335–353.
- [3] W. Miehle, *Link Length Minimization in Networks*. Opns. Res. **6** (1958), 232–243.
- [4] L.M. Ostresh, *The Multifacility Location Problem: Applications and Descent Theorems*. J. Region. Sci. **17** (1977), 409–419.

- [5] V. Preda and C. Niculescu, *On a hyperboloid approximation procedure for a perturbed generalized euclidean multifacility location problem*. Proceedings of the 7th Balkan Conference on Operational Research, București, 2007, 159–163.
- [6] V. Preda, I.M. Stancu-Minasian and E. Koller, *On optimality and duality for multiobjective programming problems involving generalized d -type-I and related n -set functions*. Journal of Mathematical Analysis and Applications **283**(1) (2003), 114–128.
- [7] V. Preda and A. Batatorescu, *On duality for minmax generalized B -vex programming involving n -set functions*. Journal of Convex Analysis **9**(2) (2002), 609–623.
- [8] V. Preda and I. Chitescu, *On constraint qualification in multiobjective optimization problems: Semidifferentiable case*. Journal of Optimization Theory and Applications **100**(2) (1999), 417–433.
- [9] V. Preda, *On sufficiency and duality for generalized quasi-convex programs*. Journal of Mathematical Analysis and Applications **181**(1) (1994), 77–88.
- [10] J.B. Rosen and G.L. Xue, *On the Convergence of a Hyperboloid Approximation Procedure for the Perturbed Euclidean Multifacility Location Problem*. Opns. Res. **41**(6) (1993), 1164–1171.
- [11] E. Weiszfeld, *Sur le Point par Lequel le Somme des Distances de n Points Donnes est Minimum*. Tohoku Math. J. **43** (1937), 355–386.

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