## SURESH CHANDRA

## Decomposition principle for linear fractional functional programs

Revue française d'informatique et de recherche opérationnelle, tome 2, n ${ }^{\circ}$ R2 (1968), p. 65-71
[http://www.numdam.org/item?id=M2AN_1968_2_2_65_0](http://www.numdam.org/item?id=M2AN_1968_2_2_65_0)
© AFCET, 1968, tous droits réservés.
L'accès aux archives de la revue « Revue française d'informatique et de recherche opérationnelle »implique l'accord avec les conditions générales d'utilisation (http://www.numdam.org/conditions). Toute utilisation commerciale ou impression systématique est constitutive d'une infraction pénale. Toute copie ou impression de ce fichier doit contenir la présente mention de copyright.

## Numdam

Article numérisé dans le cadre du programme
Numérisation de documents anciens mathématiques
http://www.numdam.org/

# DEGOMPOSITION PRINCIPLE FOR LINEAR FRACTIONAL FUNGTIONAL PROGRAMS 

by Suresh Chandra<br>Department of Mathematics, Indian Institute of Technology, Kanpur (India)

Résumé. — Le «Principe de décomposition pour des programmes linéaires» est généralisé au cas des programmes fractionnaires. On démontre que pour résoudre un probleme compliqué de programmation ayant une fonction fractionnaire, on doit résoudre une série de problèmes de programmes linéaires qui sont beaucoup plus simples que le problème original. Ce principe peut être appliqué à quelques problèmes spéciaux de programmation fractionnelle.

## INTRODUCTION

From practical point of view, it becomes necessary to consider the large structured programming problems, but even if it is theoretically possible to solve this problem, in practice it is not always so. There are certain limitations which restrict the endeavours of the analyst. Chief among these limitations is the problem of dimensionality. This suggests the idea of developing methods of solution that should not use simultaneously all the data of the problem. One such approach is the decomposition principle due to Dantzig and Wolf [1] for Linear programs. This principle requires the solution of a series of linear programming problems of smaller size than the original problem. The problem considered in [1] has the following structure :

Maximize

$$
\begin{equation*}
Z=\sum_{j=1}^{r} \mathbf{C}_{j}^{\prime} \mathbf{x}_{j} \tag{1}
\end{equation*}
$$

Subject to

$$
\begin{array}{rlrl}
\sum_{j=1}^{r} A_{j} \mathbf{x}_{j} & =\mathbf{b}_{0} & & \\
B j \mathbf{x}_{j} & =\mathbf{b}_{j} \quad & (j=1,2, \ldots r) \\
\mathbf{x}_{j} & \geqslant 0 \quad & (j=1,2, \ldots r) \tag{4}
\end{array}
$$

where (i) $A_{j}$ and $B_{j}$ are matrices of order $\left(m_{0} \times n_{j}\right)$ and ( $m_{j} \times n_{j}$ ) respectively.
(ii) $\mathbf{X}_{j}$ and $\mathbf{C}_{j}$ are vectors having $n_{j}$ components each.
(iii) $\mathbf{b}_{0}$ is an $m_{0}$ vector and $\mathbf{b}_{j}(j=1,2, \ldots, r)$ is an $m_{j}$ vector.

Williams [2] gave a treatment of the transportation problem by Decomposition. The decomposition of Non linear programming problems was also considered by a number of authors, mainly, Rosen [3], Whinston [4], Variya [5] and others.

Here a large structured linear fractional functionals programming (L.F.F.P.) problem is considered with the constraints (2), (3) and (4), and it is shown that for solving this problem we have to solve a series of smaller sized linear programming problems. The mathematical formulation of the problem is as follows :

Maximize

$$
\begin{equation*}
Z=\frac{\left[\sum_{j=1}^{r} \mathbf{C}_{j}^{\prime} \mathbf{x}_{j}+u\right]}{\left[\sum_{j=1}^{r} \mathbf{d}_{j}^{\prime} \mathbf{x}_{j}+v\right]} \tag{5}
\end{equation*}
$$

Subject to constraints (2) and (3) and (4), where $\mathbf{d}_{j}$ is a vector having $n_{j}$ components and $u \& v$ are given scalars. Apart from the usual assumptions of L.F.F.P., it is assumed that the set $S_{j}$ of all $\mathbf{X}_{j} \geqslant 0$ satisfying $B_{j} \mathbf{X}_{\boldsymbol{j}}=\mathbf{b}_{\boldsymbol{j}}$ is a convex polyhedron. We shall call this as Problem (A).

The paper is dealt into three sections. Section I considers the preliminaries and the main principle is developed in Section II. In Section III, its application is discussed in some special problems.

## SECTION I

## Preliminaries :

(i) Any point in a convex polyhedron can be written as a convex linear combination of the extreme points and conversely every such point belongs to the polyhedron [6].
(ii) For the L.F.F.P. problem

Maximize

$$
Z=\frac{\mathbf{C}^{\prime} \mathbf{x}+C_{0}}{\mathbf{d}^{\prime} \mathbf{x}+d_{0}}
$$

Subject to

$$
\begin{array}{r}
A \mathbf{x}=\mathbf{b} \\
\mathbf{x} \geqslant 0
\end{array}
$$

the optimality criterion given by Kantiswarup [7] is that :

$$
\Delta_{j}=\left[V_{2}\left(C_{j}-Z_{j}^{(1)}\right)-V_{1}\left(d_{j}-z_{j}^{(2)}\right)\right] \leqslant 0
$$

for $j=1,2, \ldots, n$. Here $A$ is a ( $m \times n$ ) matrix, $\mathbf{C} \& \mathbf{d}$ are vectors having $n$ components each, $C_{0}$ and $d_{0}$ are given scalars. If $B$ is the basis matrix, and $\mathbf{C}_{B}$ and $\mathbf{d}_{B}$ are cost vectors corresponding to this basis matrix, then :

$$
\begin{gathered}
V_{1}=\mathbf{C}_{B}^{\prime} B^{-1} \mathbf{b}+C_{0} ; \quad V_{2}=\mathbf{d}_{B}^{\prime} B^{-1} \mathbf{b}+d_{0} \\
\mathbf{Z}_{j}^{(1)}=\mathbf{C}_{B}^{\prime} \mathbf{y}_{j} ; \quad \mathbf{Z}_{j}^{(2)}=\mathbf{d}_{B}^{\prime} \mathbf{y}_{j} ; \quad \mathbf{y}_{j}=B^{-1} \mathbf{a}_{j} \\
A=\left[\mathbf{a}_{1}, \mathbf{a}_{2}, \ldots, \mathbf{a}_{n}\right]
\end{gathered}
$$

## SECTION II

Let $\mathbf{x}_{k j}^{0}$ denote the extreme points of the convex set of feasible solutions to $B_{j} \mathbf{x}_{j}=\mathbf{b}_{j}, \mathbf{x}_{j} \geqslant 0(j=1,2, \ldots r)$. Since the set $S_{j}$ is a convex polyhedron, we have $\mathbf{x}_{j} \in S_{j}$ if and only if there exist $\gamma_{k j}$ such that

$$
\begin{gather*}
\mathbf{x}_{j}=\sum_{k=1}^{h_{j}} \gamma_{k j} \mathbf{x}_{k j}^{0} \\
\gamma_{k j} \geqslant 0 \quad\left(k=1,2, \ldots, h_{j}\right) \\
\sum_{k=1}^{h_{j}} \gamma_{k j}=1 \tag{6}
\end{gather*}
$$

In view of (5), the problem $(A)$ is equivalent to the following problem :
Maximize

$$
Z_{-}=\frac{\left[\sum_{j=1}^{r} \sum_{k=1}^{h_{i}} \gamma_{k j} \mathbf{C}_{j}^{\prime} \mathbf{x}_{k j}^{0}+u\right]}{\left[\sum_{j=1}^{r} \sum_{k=1}^{h_{i}} \gamma_{k j} \mathbf{d}_{j}^{\prime} \mathbf{x}_{k j}^{0}+v\right]}
$$

Subject to,

$$
\begin{align*}
& \sum_{j=1}^{r} \sum_{k=1}^{h_{i}} \gamma_{k j} A_{j} \mathbf{x}_{k j}^{0}=\mathbf{b}_{0} \\
& \sum_{k=1}^{h_{j}} \gamma_{k j}=1, \quad \gamma_{k j} \geqslant 0 \tag{7}
\end{align*}
$$

Let us write :

$$
\begin{aligned}
\mathbf{p}_{k j} & =A_{j} \mathbf{x}_{k j}^{0} ; \quad f_{k j}^{(1)}=\mathbf{C}_{j}^{\prime} \mathbf{x}_{k j}^{0} \\
f_{k j}^{(2)} & =\mathbf{d}_{j}^{\prime} \mathbf{x}_{k j}^{0} \quad\left(j=1,2, \ldots r ; k=1,2, \ldots h_{j}\right) \\
\mathbf{q}_{k j} & =\left(\mathbf{p}_{k j}, \mathbf{e}_{j}\right) ; \quad \mathbf{b}=\left(\mathbf{b}_{0}, \mathbf{1}^{\prime}\right)
\end{aligned}
$$

Where $e_{j}$ is the $j^{\text {th }}$ unit vector having $r$ - components and $1^{\prime}$ is a $r$-component vector, each component being 1 . Then the above problem becomes :

Maximize

$$
Z=\frac{\left[\sum_{j=1}^{r} \sum_{k=1}^{h_{j}} f_{k j}^{(1)} \gamma_{k j}+u\right]}{\left[\sum_{j=1}^{r} \sum_{k=1}^{h_{i}} f_{k j}^{(2)} \gamma_{k j}+v\right]}
$$

Subject to,

$$
\begin{gathered}
\sum_{j=1}^{r} \sum_{k=1}^{h_{j}} \gamma_{k j} \mathbf{q}_{k j}=\mathbf{b} \\
\gamma_{k j} \geqslant 0
\end{gathered}
$$

We call this as problem ( $B$ ). It is to be noted that problem $(B)$ has $\left(m_{0}+r\right)$ constraints while problem $(A)$ has $\sum_{j=0}^{r} m_{j}$ constraints, thus in general requiring a smaller basis than problem $(A)$. We shall show that it is not necessary to generate every extreme point, before the problem is solved. $\mathbf{p}_{k j}, f_{k j}^{(1)}$ and $f_{k j}^{(2)}$ can be generated, as they are used.

We now apply result (ii) of Section I to the problem (B). Let $B$ is any basis matrix (of order ( $m_{0}+r$ ) for problem ( $B$ ) and $\gamma_{B}=B^{-1} \mathbf{b}$ is the basic feasible solution. Let :

$$
\sigma^{(1)}=\left(\sigma_{1}^{(1)}, \sigma_{2}^{(1)}\right)=\left(\mathbf{f}_{B}^{(1)}\right)^{\prime} B^{\dashv}
$$

and

$$
\sigma^{(2)}=\left(\sigma_{1}^{(2)}, \sigma_{2}^{(2)}\right)=\left(\mathbf{f}_{B}^{(2)}\right)^{\prime} B^{-1} \quad \text { where } \quad \sigma_{1}^{(1)}
$$

contains the first $m_{0}$ components of $\sigma^{(1)}$ and $\sigma_{i}^{(2)}$ contains the last $r$ components of $\boldsymbol{\sigma}^{(1)}$. Similarly $\boldsymbol{\sigma}^{(2)}$ is partitioned. Then

$$
\begin{equation*}
\Delta_{k j}=\left[V_{2}\left(f_{k j}^{(1)}-Z_{k j}^{(1)}\right)-V_{1}\left(f_{k j}^{(2)}-Z_{k j}^{(2)}\right)\right] \tag{8}
\end{equation*}
$$

but as in [7]

$$
\left(f_{k j}^{(1)}-Z_{k j}^{(1)}\right)=\left(\mathbf{C}_{j}^{\prime}-\sigma_{1}^{(1)} A_{j}\right) \mathbf{x}_{k j}^{0}-\sigma_{2 j}^{(1)}
$$

where $\sigma_{2 j}^{(1)}$ is the $j^{\text {th }}$ component of $\sigma_{2}^{(1)}$. Similarly

$$
\left(f_{k j}^{(2)}-Z_{k j}^{(2)}\right)=\left(\mathbf{d}_{j}^{\prime}-\sigma_{1}^{(2)} A_{j}\right) \mathbf{x}_{k j}^{0}-\sigma_{2 j}^{(2)}
$$

Hence from (8) :

$$
\begin{equation*}
\Delta_{k j}=\left[V_{2}\left(\mathbf{C}_{j}^{\prime}-\sigma_{1}^{(1)} A_{j}\right)-V_{1}\left(\mathbf{d}_{j}^{\prime}-\sigma_{1}^{(2)} A_{j}\right)\right] \mathbf{x}_{k j}^{0}+\left[V_{1} \sigma_{2 j}^{(2)}-V_{2} \sigma_{2 j}^{(1)}\right] \tag{9}
\end{equation*}
$$

where $V_{1}$ and $V_{2}$ denote respectively the values of numerator and denominator of the objective function of problem ( $B$ ) at the basic feasible solution $\gamma_{B}=B^{-1} b$.

Now Max $\Delta_{k j} \leqslant 0$, then the solution under consideration is optimal, all $k$ \& $j$ otherwise more iterations are required, but

$$
\begin{equation*}
\left.\underset{k \& j}{\operatorname{Max}_{k j}} \Delta_{k}=\underset{k}{\operatorname{Max}} \Delta_{k 1}, \ldots, \operatorname{Max}_{k} \Delta_{k r}\right] \tag{10}
\end{equation*}
$$

From (9), for a given $j, \operatorname{Max} \Delta_{k j}$ occurs at an extreme point of $S_{j}$. Let $Z_{j}=\left[V_{2}\left(\mathbf{C}_{j}^{\prime}-\sigma_{1}^{(1)} A_{j}\right)-V_{1}\left(\mathbf{d}_{j}^{\prime}-\sigma_{1}^{(2)} A_{j}\right)\right] \mathbf{x}_{j}$.

Since each extreme point $\mathbf{x}_{k j}^{0}$ is a basic feasible solution to $B_{j} \mathbf{x}_{j}=\mathbf{b}_{j}$ we have :

$$
\underset{k}{\operatorname{Max}} \Delta_{k j}=\left[V_{1} \sigma_{2 j}^{(2)}-V_{2} \sigma_{2 j}^{(1)}\right]+Z_{j}^{0}
$$

where $Z_{j}^{0}$ is the optimal value of the $j^{\text {th }}(j=1,2, \ldots, r)$ problem :
Maximize $Z_{j}$
Subject to

$$
\begin{align*}
B_{j} \mathbf{x}_{j} & =\mathbf{b}_{j} \\
\mathbf{x}_{j} & \geqslant 0 \tag{11}
\end{align*}
$$

Moreover, an optimal basic solution to (11) gives an extreme point $\mathbf{x}_{k j}^{0}$ for which the corresponding $\Delta k_{j}$ is maximum over $k$. Knowing this $\mathbf{x}_{k j}^{0}$ the corresponding $\mathbf{p}_{k j}, f_{k j}^{(1)} \& f_{k j}^{(2)}$ can be generated accordingly. Now

$$
\begin{align*}
\operatorname{Max}_{\operatorname{all} k j} \Delta_{k j} & =\underset{j}{\operatorname{Max}}\left[Z_{j}^{0}+V_{1} \sigma_{2 j}^{(2)}-V_{2} \sigma_{2 j}^{(1)}\right] \\
& =Z_{s}^{0}+V_{1} \sigma_{2 s}^{(2)}-V_{2} \sigma_{2 s}^{(1)} \tag{12}
\end{align*}
$$

where the max is taken, say, for $j=S$.
If $\mathbf{x}_{r s}^{0}$ is an optimal extreme point of (11) for $j=S$, and

$$
\mathbf{p}_{r s}=A_{s} \mathbf{x}_{r s}^{0}, \mathbf{q}_{r s}=\left(\mathbf{p}_{r s}, \mathbf{e}_{s}\right)
$$

then $\mathbf{q}_{r s}$ enters the basis at the next iteration. The vector to leave the basis is determined in the usual way.

Next the problem $(B)$ is transformed to get the new values of $B^{-1}, \sigma^{(1)}, \sigma^{(2)}$ and $\gamma_{B}$. As before the new values of $\sigma^{(1)}$ and $\sigma^{(2)}$ are used to determine a new set of $r$ linear programming problems. By solving theses $r$ new linear programming problems, we determine the vector to enter the basis as before. In the absence of degeneracy (of course degeneracy can be handled in the usual way), the above process terminates in a finite number of steps by the theory of simplex method for L.F.F.P.

## SECTION III

As in case of linear programming [6], [8] the technique developed in Section II, can be applied to the following L.F.F.P. Problems :

## I. - Generalized L.F.F.P. Problem

$$
\begin{equation*}
\operatorname{Max} Z=\frac{\left[\sum_{j=1}^{r} c_{j \varkappa_{j}}+c_{0}\right]}{\left[\sum_{j=1}^{r} d_{j} \varkappa_{j}+d_{0}\right]} \tag{12}
\end{equation*}
$$

Subject to

$$
\begin{array}{r}
\sum_{j=1}^{r} x_{j} \mathbf{a}_{j}=\mathbf{b} \\
x_{j} \geqslant 0
\end{array}
$$

where the vectors $a_{j}$ are not specified but they are restricted such that $B_{j} \mathbf{a}_{j} \leqslant \mathbf{b}_{j}(j=1,2, \ldots, r)$. It is assumed that these inequalities determine a convex polyhedron ([6]).

## II. - L.F.F.P. with upper bonds on the variables

Maximize

$$
Z=\frac{\left[\mathbf{c}_{1}^{\prime} \mathbf{x}_{1}+\mathbf{c}_{2}^{\prime} \mathbf{x}_{2}+u\right]}{\left[\mathbf{d}_{1}^{\prime} \mathbf{x}_{1}+\mathbf{d}_{2}^{\prime} \mathbf{x}_{2}+v\right]}
$$

Subject to

$$
\begin{align*}
A_{1} \mathbf{x}_{1}+A_{2} \mathbf{x}_{2} & =b \\
I \mathbf{x}_{1} & \leqslant \mathbf{h} \\
\mathbf{x}_{1}, \mathbf{x}_{2} & \geqslant 0 \tag{13}
\end{align*}
$$

where $A_{1}, A_{2}$ are matrices of order ( $m \times n_{1}$ ) and ( $m \times n_{2}$ ) respectively and $I$ is a ( $n_{1} \times n_{1}$ ) identity matrix. This problem can be solved by using the technique of Section II, as in [8].

## ACKNOWLEDGEMENTS

I am extremely thankful to Prof. J. N. Kapur and Dr. S. K. Gupta, Department of Mathematics, Indian Institute of Technology, Kanpur, for their continued help and inspiring guidance.

## REFERENCES

[1] Dantzig, C. B. and Philip Wolf, «Decomposition Principle for Linear Programs », Operations Research, vol. 8 (1960), pp. 101-111.
[2] Williams, A. C., «A Treatment of the Transposition problem by Decomposition», J. Soc. Indust. and App. Math., 10 (1962), pp. 35-48.
[3] Rosen, J. B., "Convex Partition Programming», Recent Advances in Math. Programming (1963).
[4] Whinston, A., «A dual decomposition algorithm for Quadratic Programming », Cahiers du centre d'études Research Operationnelle, 6 (188-201) (1964).
[5] Variya, P., «Decomposition of large scale systems », SIAM, vol. 4 (1966), nº 1.
[6] Hadley, G., Linear Programming, Addison-Wesley Publishing Company, Inc. (1963).
[7] Kantiswarup, «Linear fractional functionals Programming 》, Operations Research, vol. 13, n ${ }^{0} 6$ (1965), pp. 1029-1036.
[8] Hadley, G., Non-linear and Dynamic Programming, Addison-Wesley Publishing Company, Inc. (1964).

