

**Report n.70**

**An algorithm for a non-differentiable non-linear  
fractional programming problem**

**Anna MARCHI - Claudio SODINI**

**Pisa, 1993**

**This research was supported in part by the Ministry of Public Education.**

# AN ALGORITHM FOR A NON-DIFFERENTIABLE NON-LINEAR FRACTIONAL PROGRAMMING PROBLEM(\*)

**Anna Marchi** - Dept. of Statistics and Applied Mathematics, Univ. of Pisa

**Claudio Sodini** - Institute of Mathematics "E.Levi", University of Parma

## Abstract

The problem of minimizing a non-differentiable fractional function on a polytope is considered. The numerator is the sum of a linear function and the square root of a convex quadratic form while the denominator is a linear function. Patkan and Stancu-Minasian have studied the problem and, for the case of a bounded feasible region, they have proposed different approaches for solving it. In this paper we will be discussing a finite algorithm, which solves the problem by means of a parametric quadratic programming, even when the feasible region is unbounded.

---

(\*) The paper has been discussed jointly by the authors, A.Marchi has developed sections 3 and 4, C.Sodini has developed sections 1 and 2.

## 1. The problem

The problem is:

$$(1.1) \quad \inf_{x \in S} f(x) = \frac{c^T x + c_0 + \sqrt{\frac{1}{2} x^T Q x}}{d^T x + d_0}$$

where  $Q$  is a symmetric positive definite  $n \times n$  matrix,  $c, d \in \mathbb{R}^n$ ,  $c_0, d_0 \in \mathbb{R}$ ,  $S = \{x \in \mathbb{R}^n: Ax \geq b\}$ <sup>1</sup>,  $A$  is an  $m \times n$  matrix and  $b \in \mathbb{R}^m$ . We will suppose that  $d^T x + d_0 > 0, \forall x \in S$ .

We will consider vectors  $(c^T, c_0)$  and  $(d^T, d_0)$  linearly independent, because, if  $(c^T, c_0) = \lambda (d^T, d_0)$  with  $\lambda \in \mathbb{R}$ , problem (1.1) becomes:

$$\inf_{x \in S} f(x) = \frac{\lambda (d^T x + d_0) + \sqrt{\frac{1}{2} x^T Q x}}{d^T x + d_0} = \lambda + \frac{\sqrt{\frac{1}{2} x^T Q x}}{d^T x + d_0}$$

and this problem has been studied and solved in [1].

## 2. Theoretical properties

In [2,3,4] Patkar and Stancu-Minasian proved that the objective function  $f(x)$  is "explicitly" quasi-convex. This property implies that any local minimum is also global.

The function  $f(x)$  is non-differentiable in  $x=0$ . This implies that "a priori" methods based on validation of Kuhn -Tucker (K-T) conditions cannot be applied. We will show that it is possible to define a procedure, based on validation of K-T conditions, which solves the problem in a finite number of steps.

For problem (1.1) the following three cases can occur:

- there exists an  $x^{opt} \in S$  such that  $\inf \{f(x): x \in S\} = f(x^{opt})$ ;
- $\inf \{f(x): x \in S\} = L > -\infty$ , but the inf is not attained; then there exists a half-line  $\{x = x_0 + k u, k \geq 0, x_0 \in S\} \subset S$  such that:  
 $\lim_{k \rightarrow +\infty} f(x_0 + k u) = L$ ;
- $\inf \{f(x): x \in S\} = -\infty$ ; i.e., there exists a half-line  $\{x = x_0 + k u, k \geq 0, x_0 \in S\} \subset S$  such that:  
 $\lim_{k \rightarrow +\infty} f(x_0 + k u) = -\infty$ .

These three cases will be shown implicitly by the algorithm proposed in section 4.

---

<sup>1</sup>We will suppose that  $S$  is non empty and the vertices of  $S$  are non degenerate.

Set  $C_0 = c^T x_0 + c_0$  and  $D_0 = d^T x_0 + d_0$ .

**Remark 2.1:** Let us note that if  $S$  is a bounded region only case a) occurs. If  $S$  is unbounded, let us consider a half-line  $\{x = x_0 + k u, k \geq 0, x_0 \in S\} \subset S$  and denote with  $\phi(k)$  the restriction of  $f(x)$  on this half-line, we have:

i) if  $d^T u > 0$  then  $\lim_{k \rightarrow +\infty} \phi(k) = \frac{c^T u + \sqrt{\frac{1}{2} u^T Q u}}{d^T u} = L_1$ ;

ii) if  $d^T u = 0$  and  $c^T u + \sqrt{\frac{1}{2} u^T Q u} = 0$  then  $\lim_{k \rightarrow +\infty} \phi(k) = \frac{C_0}{D_0} + \frac{x_0^T Q u}{D_0 \sqrt{2 u^T Q u}} = L_2$ ;

iii) if  $d^T u = 0$  and  $c^T u + \sqrt{\frac{1}{2} u^T Q u} < 0$  then  $\lim_{k \rightarrow +\infty} \phi(k) = -\infty$ ;

iv) if  $d^T u = 0$  and  $c^T u + \sqrt{\frac{1}{2} u^T Q u} > 0$  then  $\lim_{k \rightarrow +\infty} \phi(k) = +\infty$ .

By applying the Charnes-Cooper transformations  $y = x t$ ,  $t = \frac{1}{d^T x + d_0}$  to the problem (1.1), we obtain :

$$(2.1) \quad \inf_{(y,t) \in R} \varphi(y,t) = c^T y + c_0 t + \sqrt{\frac{1}{2} y^T Q y}$$

where  $R = \{(y, t) \in \mathbb{R}^{n+1} : Ay - bt \geq 0, d^T y + d_0 t = 1, t > 0\}$ .

The following theorems state some conditions which will allow us to solve problem (1.1) through problem:

$$(2.2) \quad \inf_{(y,t) \in R'} \varphi(y,t) = c^T y + c_0 t + \sqrt{\frac{1}{2} y^T Q y}$$

where  $R' = \{(y, t) \in \mathbb{R}^{n+1} : Ay - bt \geq 0, d^T y + d_0 t = 1, t \geq 0\}$ .

**Theorem 2.1:** To each ray  $u$  which verifies condition i) of Remark 2.1 corresponds a  $(y,0) \in R'$  such that  $\varphi(y,0) = L_1$  and viceversa.

**Proof:** If  $u$  satisfies conditions i) of Remark 2.1, then

$$Au \geq 0, Ax_0 \geq b, d^T u > 0 \text{ and } \lim_{k \rightarrow +\infty} \phi(k) = \frac{c^T u + \sqrt{\frac{1}{2} u^T Q u}}{d^T u} = L_1;$$

it follows that in problem (2.2):

$$(u / d^T u, 0) \in R' \text{ and } \varphi(u / d^T u, 0) = L_1.$$

Viceversa, if  $(y,0) \in R'$  then

$$Ay \geq 0, d^T y = 1, \varphi(y,0) = c^T y + \sqrt{\frac{1}{2} y^T Q y};$$

it follows that:

$$A(x_0 + k y) \geq b, x_0 \in S, \forall k \geq 0 \text{ and } \lim_{k \rightarrow +\infty} \phi(k) = \frac{c^T y + \sqrt{\frac{1}{2} y^T Q y}}{d^T y} = \phi(y, 0)$$

being  $d^T y = 1$ . This completes the proof.

Let us denote with  $\psi(\theta)$  the restriction of  $\phi(y, t)$  on  $(y, t) = (y_0, t_0) + \theta (\omega, \delta), \theta \geq 0$ :

**Theorem 2.2:** To each point  $x_0$  and ray  $u$  which verify condition ii) of Remark 2.1 corresponds a half-line  $\{(y, t) = (y_0, t_0) + \theta (\omega, \delta), \theta \geq 0, (y_0, t_0) \in R'\} \subset R'$  such that:

$$\lim_{k \rightarrow +\infty} \phi(k) = \lim_{\theta \rightarrow +\infty} \psi(k) = L_2$$

and viceversa.

**Proof:** If  $x_0$  and  $u$  satisfy conditions ii) of Remark 2.1, then

$$Au \geq 0, Ax_0 \geq b, d^T u = 0, c^T u + \sqrt{\frac{1}{2} u^T Q u} = 0 \text{ and } \lim_{k \rightarrow +\infty} \phi(k) = L_2;$$

It follows that in problem (2.2) there exists the corresponding half-line with:  $y_0 = x_0/D_0, t_0 = 1/D_0, \omega = u/D_0$  and  $\delta = 0$  such that:

$$\lim_{\theta \rightarrow +\infty} \psi(\theta) = L_2.$$

Viceversa, we must prove that if:

$$\lim_{\theta \rightarrow +\infty} \psi(\theta) = L_2$$

then there exists a half-line in  $S$  such that condition ii) of remark 2.1 is verified. Let us consider a half-line  $(y, t) = (y_0, t_0) + \theta (\omega, \delta), \theta \geq 0$  such that:

$$Ay_0 - bt_0 \geq 0, A\omega - b\delta \geq 0, d^T y_0 + d_0 t_0 = 1, d^T \omega + d_0 \delta = 0, \text{ then}$$

$$\text{if } c^T \omega + c^T \delta + \sqrt{\frac{1}{2} \omega^T Q \omega} = 0, \lim_{\theta \rightarrow +\infty} \psi(\theta) = c^T y_0 + c^T t_0 + \frac{y_0^T Q \omega}{\sqrt{2 \omega^T Q \omega}}.$$

Let us note that  $\delta$  must equal zero, in fact if  $\delta \neq 0$  then:

$$A \omega / \delta \geq b, \omega / \delta \in S, d^T \omega / \delta + d_0 = 0, \text{ contradicting the hypothesis } d^T x + d_0 > 0,$$

$A x \in S$ . It follows that  $y_0/t_0 \in S, \omega/t_0$  is a ray of  $S$  such that :

$$\lim_{k \rightarrow +\infty} \phi(k) = \lim_{\theta \rightarrow +\infty} \psi(k) = L_2$$

This completes the proof.

**Theorem 2.3:** To each point  $x_0$  and ray  $u$  which verify condition iii) of Remark 2.1 corresponds a half-line  $\{(y, t) = (y_0, t_0) + \theta (\omega, \delta), \theta \geq 0, (y, t) \in R'\} \subset R'$  such that:

$$\lim_{k \rightarrow +\infty} \phi(k) = \lim_{\theta \rightarrow +\infty} \psi(k) = -\infty$$

and viceversa.

**Proof:** Similar to proof of theorem 2.2.

**Remark 2.2:** As a consequence of the previous theorems we have that:

- 1) if  $(y', t')$  is a finite optimal solution of problem (2.2) then two cases can occur:
  - $t' > 0$ ; in this case,  $x^{opt} = y'/t'$  is the optimal solution of problem (1.1);
  - $t' = 0$ ; in this case, problem (1.1) is lower bounded on  $S$  but the inf is not attained, in fact,  $\inf\{f(x): x \in S\} = \phi(y', 0)$  on ray  $y'$ ;
- 2) if problem (2.2) is unbounded then problem (1.1) is unbounded;
- 3) if problem (2.2) is lower bounded, but the inf is obtained on the half-line  $\{(y, t) = (y', t') + \theta(\omega, \delta), \theta \geq 0, (y, t) \in R'\}$  then also problem (1.1) is lower bounded and  $\inf\{f(x): x \in S\} = \inf\{\phi(y, t): (y, t) \in R'\} = c^T y' + c_0 t' + \sqrt{\frac{1}{2} y'^T Q y'}$  on half-line  $\{x = y'/t' + k w'/t', k \geq 0\} \subset S$ .

In [5] a procedure has been proposed to solve the following problem:

$$(2.3) \quad \min g(z) = q^T z + k_0 \sqrt{\frac{1}{2} z^T H z}, \quad z \in S'$$

when  $H$  is a symmetric positive definite  $p \times p$  matrix,  $q \in \mathbb{R}^p$ ,  $k_0 \in \mathbb{R}^+$ ,  $S' = \{z \in \mathbb{R}^p: A' z \geq b'\}$ ,  $A'$  is an  $m' \times p$  matrix and  $b' \in \mathbb{R}^{m'}$ . Let us note that it is not possible to directly apply this procedure to solve problem (2.2), since if we set:

$$z = \begin{bmatrix} y \\ t \end{bmatrix}, \quad q = \begin{bmatrix} c \\ c_0 \end{bmatrix}, \quad H = \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix}, \quad k_0 = 1,$$

$$A' = \begin{bmatrix} A & -b \\ d^T & d_0 \\ 0 & 1 \end{bmatrix}, \quad b' = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \text{and } p = n+1$$

$H$  is semi-definite positive. The procedure proposed in [5] solves problem (2.3) by means of parametric quadratic programming. If we apply this procedure, we may have the following results for problem (2.3):

- 1) there exists an optimal solution  $z_{opt} \in S'$ ;
- 2) problem (2.3) is not lower bounded;
- 3) problem (2.3) is lower bound but the inf is not attained.

The following is a brief description of this procedure, called SO (see [5] for further information):

**Step 0:** Determine  $H^{-1}$ .

If  $(2q^T H^{-1} q)^{1/2} < k_0$  and  $b' \leq 0$ , then set  $z_{opt} = 0$  and STOP.

If  $(2q^T H^{-1} q)^{1/2} = k_0$  and  $S'(\theta) = \{\theta: A' z(\theta) \geq b', \theta \leq 0\} \neq \emptyset$  where

$z(\theta) = \frac{\theta}{q^T H^{-1} q} H^{-1} q$  then set  $z_{\text{opt}} = z(\theta)$  for  $\theta \in S'(\theta)$  and STOP.

If  $(2 q^T H^{-1} q)^{1/2} > k_0$  and  $\inf S'(\theta) = -\infty$  then problem (2.2) is unbounded and STOP.

If  $(2 q^T H^{-1} q)^{1/2} > k_0$  and  $\inf S'(\theta) = \theta' \neq 0 > -\infty$  then set  $k=1$ ,  $z^{(k)} = z(\theta')$ ,  $\theta^0 = q^T z^{(k)}$  and go to Step 2.

Otherwise, go to Step 1.

**Step 1:** Set  $k=1$ , let  $z^{(k)}$  be the optimal solution of the linear problem  $\min q^T z$ ,  $z \in S'$ . If  $z^{(k)} = 0$  then set  $z_{\text{opt}} = 0$  and STOP.

If  $z^{(k)} \neq 0$  and  $S' \cap \{ z : q^T z = q^T z^{(k)} \} = \{ z^{(k)} \}$  then set  $\theta^0 = q^T z^{(k)}$  and go to Step 2.

If  $z^{(k)} \neq 0$  and  $S' \cap \{ z : q^T z = q^T z^{(k)} \} \neq \{ z^{(k)} \}$  then solve  $P'(\theta) = \{ \min z^T H z, z \in S', q^T z = \theta \}$  with  $\theta = q^T z^{(k)}$ ; let  $z'$  be the optimal solution of this problem, set  $z^{(k)} = z'$  and  $\theta^0 = q^T z^{(k)}$  and go to Step 2.

If  $\{ \min q^T z, z \in S' \} = -\infty$ , determine a solution  $z' \in S'$  such that  $q^T z' < 0$  and let  $z^{(k)}$  be the optimal solution of  $P'(q^T z')$ , set  $\theta^0 = q^T z^{(k)}$  and go to Step 2.

**Step 2:** Let  $M' z^{(k)} = b'_M$  the equations of the constraints binding at  $z^{(k)}$ . If  $z^{(k)}$  is not a vertex, select from the matrix  $B' = \begin{bmatrix} M' \\ q^T \end{bmatrix}$  the submatrix  $B = \begin{bmatrix} M \\ q^T \end{bmatrix}$  of maximum rank and go to Step 2. Otherwise, select a feasible basis<sup>3</sup>  $B = \begin{bmatrix} M \\ q^T \end{bmatrix}$  of the matrix  $B'$  and go to Step 2.

**Step 3:** Solve the following system:

$$\begin{aligned} H z - M^T \mu - q \mu_0 &= 0 \\ (2.4) \quad M z &= b_M \\ q^T z &= \theta_0 + \theta \end{aligned}$$

$$\text{Let } z(\theta) = z^{(k)} + \alpha \theta$$

$$\mu(\theta) = \mu^{(k)} + \beta \theta$$

$$\mu_0(\theta) = \mu_0^{(k)} + \gamma \theta$$

be the solution of the system. If  $z^{(k)}$  is a vertex of  $S'$ , go to Step 5; otherwise

---

<sup>3</sup>  $B = \begin{bmatrix} M \\ q^T \end{bmatrix}$  is a feasible basis if the basic solution of the system  $M^T \mu + q \mu_0 = H z^{(k)}$  verifies conditions  $\mu \geq 0$ . In general, different bases correspond to the matrix  $B' = \begin{bmatrix} M' \\ q^T \end{bmatrix}$ .

go to Step 4.

**Step 4:** If  $\mu_0^{(k)} = 2(\theta_0 - z_0)/k_0^2$  then set  $z_{\text{opt}} = z^{(k)}$  and STOP.

If  $\mu_0^{(k)} < 2(\theta_0 - z_0)/k_0^2$  then set  $U(\theta) = H(\theta) \cap [0, +\infty)$  where  $H(\theta) = \{\theta : z(\theta) \in R\} \cap \{\theta : \mu(\theta) \geq 0\}$ ; otherwise set  $U(\theta) = H(\theta) \cap (-\infty, 0]$ ;

If  $U(\theta) = \{0\}$  then set  $z_{\text{opt}} = z^{(k)}$  and STOP. Otherwise set :

$$\theta_1 = \frac{-k_0^2 \mu_0 (2 - k_0^2 \beta) - \sqrt{2k_0^2 (2 - k_0^2 \beta) (k_0^2 \mu_0^2 - 2\beta(z_0 - \theta_0)^2)}}{k_0^2 \beta (2 - k_0^2 \beta)}$$

If  $\theta_1 \in H(\theta)$  then set  $z_{\text{opt}} = z(\theta_1)$  and STOP.

If  $\inf U(\theta) = -\infty$  and  $q^T \alpha = -k_0 \sqrt{\frac{1}{2} \alpha^T Q \alpha}$  then  $\inf \{g(z), z \in S'\} =$

$$= q^T z^{(k)} + \frac{k_0 z^{(k)T} H \alpha}{\sqrt{\frac{1}{2} \alpha^T H \alpha}} \text{ on ray } \alpha \text{ and STOP;}$$

If  $\inf U(\theta) = -\infty$  and  $q^T \alpha \neq -k_0 \sqrt{\frac{1}{2} \alpha^T Q \alpha}$  then  $\inf \{g(z), z \in S'\} = -\infty$  and STOP. Otherwise let  $\theta^{(k+1)}$  be the end point of  $U(\theta)$  different from zero, set:

$$z^{(k+1)} = z(\theta^{(k+1)})$$

$$\mu^{(k+1)} = \mu(\theta^{(k+1)})$$

$$\mu_0^{(k+1)} = \mu_0(\theta^{(k+1)})$$

If  $z^{(k+1)} = 0$  then set  $z_{\text{opt}} = 0$  and STOP. Otherwise update the constraints binding at  $z^{(k+1)}$  in system (2.4), deleting the constraint  $i$  such that  $\mu_i^{(k+1)} = 0$  and adding the constraint  $j$  such that  $a_j z^{(k)} > b_j$  and  $a_j z^{(k+1)} = b_j$  ( $a_j$  denotes the  $j$ -th row of  $A$ ), set  $k = k+1$  and go to Step 3.

**Step 5:** If there are two different bases  $B_1$  and  $B_2$  such that  $\mu_{0B_1}^{(k)} > 2(\theta_0 - z_0)/k_0^2$ ,  $\mu_{0B_2}^{(k)} < 2(\theta_0 - z_0)/k_0^2$  or  $\mu_{0B_1}^{(k)} < 2(\theta_0 - z_0)/k_0^2$ ,  $\mu_{0B_2}^{(k)} > 2(\theta_0 - z_0)/k_0^2$  then set  $z_{\text{opt}} = z^{(k)}$  and STOP.

If we have  $U(\theta) = \{0\}$  for any feasible basis  $B$ , then set  $z_{\text{opt}} = z^{(k)}$  and STOP.

Otherwise, go to Step 3.

### 3. The algorithm

As we have just observed in section 2, procedure SO cannot be directly applied to problem (2.2), since the quadratic form of this problem is semi-definite positive, in fact:

- 1) Step 0 cannot be utilized, since  $H$  is singular,
- 2) at Step 3, a linear system, which contains  $H$ , must be solved. If  $H$  is definite



positive, certainly, the system matrix is non singular, but this is not, in general, true when H is semi-definite positive as in this case.

In this section, however, we will show how it is possible to utilize however this procedure to solve problem (1.1) in the cases  $d_0 \neq 0$  or  $d_0 = 0$  and  $c_0 \neq 0$ .

Let us observe that the matrix of system (2.4), in relation to problem (2.2) is:

$$MS = \begin{bmatrix} Q & 0 & -M^T & -d & -c \\ 0 & 0 & b_M^T & -d_0 & -c_0 \\ M & -b_M & 0 & 0 & 0 \\ d^T & d_0 & 0 & 0 & 0 \\ c^T & c_0 & 0 & 0 & 0 \end{bmatrix}$$

By rearranging columns and rows, the matrix can be put in the following form:

$$MS = \begin{bmatrix} Q & -M^T & -d & -c & 0 \\ M & 0 & 0 & 0 & -b_M \\ d^T & 0 & 0 & 0 & d_0 \\ c^T & 0 & 0 & 0 & c_0 \\ 0 & b_M^T & -d_0 & -c_0 & 0 \end{bmatrix}$$

Since the sub-matrix  $[-M^T, -d, -c]$  has full rank (i.e. the columns are linearly independent) it is easy to show that, in cases  $d_0 \neq 0$  or  $d_0 = 0$  and  $c_0 \neq 0$ , MS is not singular and system (2.4) has solution.

Therefore, in cases  $d_0 \neq 0$  or  $d_0 = 0$  and  $c_0 \neq 0$ , by utilizing procedure SO, we can solve problem (2.2), starting from Step 1 instead of Step 0. Taking into account remark 2.2, the results of this procedure can be interpreted to solve problem (1.1).

In the particular case  $d_0 \neq 0$ , problem (2.2) can be transformed into an equivalent problem where the quadratic form is definite positive. Procedure SO can be applied to this new problem without any modification; in fact, by setting:

$$t = \frac{1}{d_0} (1 - d^T y)$$

problem (2.2) becomes:

$$(3.1) \quad \frac{c_0}{d_0} + \inf_{y \in T} f(y) = (c^T - \frac{c_0}{d_0} d^T) y + \sqrt{\frac{1}{2} y^T Q y}$$

$$\text{where } T = \left\{ y \in \mathbb{R}^n : \left[ A + \frac{b d^T}{d_0} \right] y \geq \frac{b}{d_0}, \frac{d^T}{d_0} y \geq \frac{1}{d_0} \right\}.$$

Problem (3.1) is equivalent to problem (2.3) by setting:

$$(3.2) \quad z=y, p=n, k_0=1, q^T = c^T - \frac{c_0}{d_0} d^T, H=Q, A' = \begin{bmatrix} A + \frac{b d^T}{d_0} \\ -\frac{d^T}{d_0} \end{bmatrix} \text{ and } b' = \begin{bmatrix} \frac{b}{d_0} \\ -\frac{1}{d_0} \end{bmatrix}$$

Taking into account previous theorems, we can interpret the result of the procedure applied to problem (3.1), for solving problem (1.1), in this way:

- 1) if problem (3.1) has optimal solution  $z_{\text{ott}}$ , then two cases can occur:
  - a)  $d^T z_{\text{ott}} \neq 1$ ; the corresponding optimal solution of problem (1.1) is given by:
 
$$x_{\text{ott}} = \frac{z_{\text{ott}} d_0}{1 - d^T z_{\text{ott}}}$$
  - b)  $d^T z_{\text{ott}} = 1$  (therefore  $t = 1/(d^T x + d_0) = 0$ ); problem (1.1) is lower bounded on  $S$  on ray  $z_{\text{ott}}$ .
- 2) if problem (3.1) is not lower bounded on  $T$ , it means that problem (1.1) is not lower bounded on  $S$ ,
- 3) if problem (3.1) is lower bounded on  $T$ , but  $\inf$  is not attained, it means that problem (1.1) is lower bounded on  $S$ .

Let us remember that problem (1.1) is non-differentiable in  $x=0$ . The following remark give us a condition to remove this problem.

**Remark 2:** If point  $x = 0$  belongs to the feasible region  $S$  (i.e.  $b \leq 0$ ), from the condition  $d^T x + d_0 > 0 \forall x \in S$ , it follows that  $d_0$  is positive. As a consequence, problem (1.1) can be transformed into problem (3.1) and procedure SO can be applied without any modification.

#### 4. An example

Let us consider the following problem:

$$(4.1) \quad \inf_{x \in S} f(x) = \frac{x_1 + x_2 + 3 + \sqrt{2x_1^2 + x_2^2}}{\frac{1}{2}x_1 + \frac{1}{2}x_2 - 1}$$

where  $S = \{ (x_1, x_2) \in \mathbb{R}^2 : x_1 - x_2 \geq 0, x_1 + x_2 \geq 3, x_2 \geq 0 \}$

The feasible region  $S$  is depicted in fig.1.

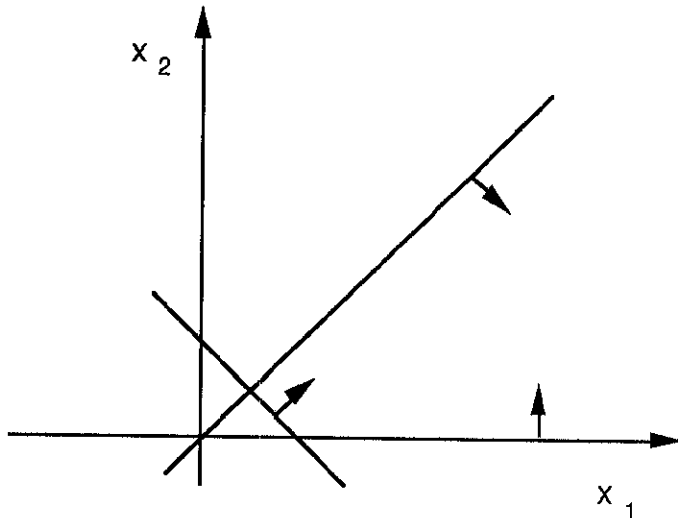


Fig.1

By applying the Charnes Cooper transformations, the problem becomes:

$$\inf_{(y_1, y_2, t) \in R} \varphi(y, t) = y_1 + y_2 + 3t + \sqrt{2y_1^2 + y_2^2}$$

where  $R = \{ (y_1, y_2, t) \in \mathbb{R}^3 : y_1 - y_2 \geq 0, y_1 + y_2 - 3t \geq 3, y_2 \geq 0, \frac{1}{2}y_1 + \frac{1}{2}y_2 - t = 1, t > 0 \}$

Taking into account that  $d_0 = -1 \neq 0$ , by setting  $t = \frac{1}{2}y_1 + \frac{1}{2}y_2 - 1$ , the problem becomes:

$$(4.2) \quad 3 + \inf_{y \in S'} \varphi(y) = \frac{5}{2}y_1 + \frac{5}{2}y_2 + \sqrt{2y_1^2 + y_2^2}$$

where  $S' = \{ (y_1, y_2) \in \mathbb{R}^2 : y_1 - y_2 \geq 0, -\frac{1}{2}y_1 - \frac{1}{2}y_2 \geq -3, y_2 \geq 0, \frac{1}{2}y_1 + \frac{1}{2}y_2 \geq 1 \}$

The feasible region  $S$  is depicted in fig.2.

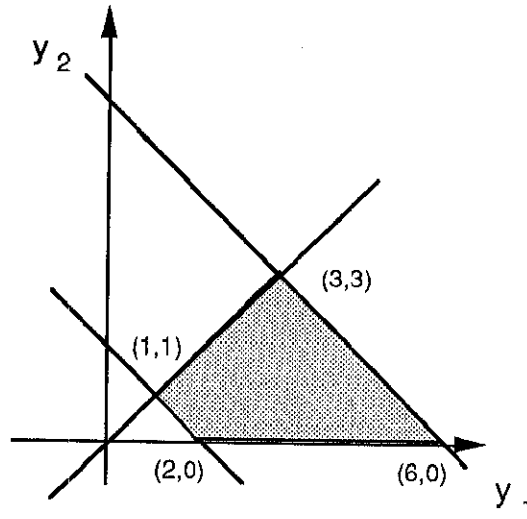


Fig.2

It is possible to apply the procedure SO to this problem, by setting:

$$z=y, \quad p=2, \quad k_0=1, \quad q = \begin{bmatrix} \frac{5}{2} \\ 2 \\ \frac{5}{2} \end{bmatrix}, \quad H = \begin{bmatrix} 4 & 0 \\ 0 & 2 \end{bmatrix}, \quad A' = \begin{bmatrix} 1 & -1 \\ \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \\ 2 & 2 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad b' = \begin{bmatrix} 0 \\ -3 \\ 1 \\ 0 \end{bmatrix}$$

By applying the algorithm we obtain the following steps:

**Step 0**, we determine  $H^{-1} = \begin{bmatrix} \frac{1}{4} & 0 \\ 0 & \frac{1}{2} \end{bmatrix}$ .

Since  $(2q^T H^{-1} q)^{1/2} = 75/8 > k_0 = 1$  and  $S'(\theta) = \{\theta : A'z(\theta) \geq b', \theta \leq 0\} = \emptyset$  where  $z(\theta) = \frac{\theta}{q^T H^{-1} q} H^{-1} q = \theta [2/15, 4/15]^T$ .

**Step 1**, set  $k=1$ , the optimal solution of the linear problem  $\min q^T z, z \in S'$  is  $z^{(1)} = (1,1) \neq 0$  and  $S' \cap \{z : q^T z = q^T z^{(k)}\} = \{(1,1)\}$  then set  $\theta^0 = q^T z^{(k)} = 5$ .

**Step 2**, we solve the following system:

$$\begin{aligned} 4z_1 - \mu_1 - \frac{5}{2}\mu_0 &= 0 \\ 2z_2 + \mu_1 - \frac{5}{2}\mu_0 &= 0 \\ z_1 - z_2 &= 0 \\ \frac{5}{2}z_1 + \frac{5}{2}z_2 &= 5 + \theta \end{aligned}$$

from which the solution:

$$z_1(\theta) = 1 + \frac{1}{5} \theta$$

$$z_2(\theta) = 1 + \frac{1}{5} \theta$$

$$\mu_1^{(1)}(\theta) = 1 + \frac{1}{5} \theta$$

$$\mu_0^{(1)}(\theta) = \frac{6}{5} + \frac{1}{5} \theta$$

**Step 4**, note that  $U(\theta) = \{0\}$  then  $z_{\text{ott}} = z^{(1)}$  is the optimal solution for problem (5.2) and the procedure stops.

Since  $d^T z_{\text{ott}} = 1$  then the  $\inf f(x)$  is not attained and  $z_{\text{ott}} = (1,1)$  is an optimal extreme ray for which  $L = 2 + \sqrt{3}$ .

## REFERENCES

- [1] Cambini, A. and C.Sodini, Un algoritmo per un problema di programmazione frazionaria non lineare derivante da un problema di selezione del portafoglio, Atti del V Convegno AMASES, Perugia ott.81;
- [2] Patkar, V. and I.M.Stancu-Minasian, Approaches for solving a class of non-differentiable non linear fractional Programming Problems, Nat. Acad. Sci. Letters, Vol.4, n.12,pp.477-479,1981;
- [3] Stancu-Minasian, I.M., Studii Si Cercet. Mat., n.28, 1976;
- [4] Stancu-Minasian, I.M., Programarea Stacastica cu mai multe functii Objectiv, Editura Acad. R.S.R., Bucuresti1980;
- [5] Sodini, C., Minimizing the sum of a linear function and the square root of a convex quadratic form, X Symposium of Op. Res. Methods of Op. Res., n.53,pp.171-182, 1985.