

# A semi-smooth Newton method for a special piecewise linear system with application to positively constrained convex quadratic programming

Nemeth, Sandor; Barrios, Jorge; Bello Cruz, Jose Yunier ; Ferreira, Orizon

DOI:

[10.1016/j.cam.2016.01.040](https://doi.org/10.1016/j.cam.2016.01.040)

License:

Creative Commons: Attribution-NonCommercial-NoDerivs (CC BY-NC-ND)

*Document Version*

Peer reviewed version

*Citation for published version (Harvard):*

Nemeth, S, Barrios, J, Bello Cruz, JY & Ferreira, O 2016, 'A semi-smooth Newton method for a special piecewise linear system with application to positively constrained convex quadratic programming', *Journal of Computational and Applied Mathematics*, vol. 301, pp. 91–100. <https://doi.org/10.1016/j.cam.2016.01.040>

[Link to publication on Research at Birmingham portal](#)

**Publisher Rights Statement:**

Validated Feb 2016

**General rights**

Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

- Users may freely distribute the URL that is used to identify this publication.
- Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
- User may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?)
- Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

**Take down policy**

While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact [UBIRA@lists.bham.ac.uk](mailto:UBIRA@lists.bham.ac.uk) providing details and we will remove access to the work immediately and investigate.

# A semi-smooth Newton method for a special piecewise linear system with application to positively constrained convex quadratic programming

J. G. Barrios <sup>\*</sup>      J.Y. Bello Cruz<sup>†</sup>      O. P. Ferreira<sup>‡</sup>      S. Z. Németh <sup>§</sup>

November 12, 2015

## Abstract

In this paper a special piecewise linear system is studied. It is shown that, under a mild assumption, the semi-smooth Newton method applied to this system is well defined and the method generates a sequence that converges linearly to a solution. Besides, we also show that the generated sequence is bounded, for any starting point, and a formula for any accumulation point of this sequence is presented. As an application, we study the convex quadratic programming problem under positive constraints. The numerical results suggest that the semi-smooth Newton method achieves accurate solutions to large scale problems in few iterations.

**Keywords:** Piecewise linear system, quadratic programming, convex set, convex cone, semi-smooth Newton method.

**2010 AMS Subject Classification:** 90C33, 15A48.

## 1 Introduction

In this paper we consider the following special piecewise linear system:

$$x^+ + Tx = b, \tag{1}$$

where, denoting by  $\mathbb{R}^{n \times n}$  the set of  $n \times n$  matrices with real entries and  $\mathbb{R}^n \equiv \mathbb{R}^{n \times 1}$  the  $n$ -dimensional Euclidean space, the data consists of  $b$  a vector in  $\mathbb{R}^n$ ,  $T$  a nonsingular matrix in  $\mathbb{R}^{n \times n}$ , the variable  $x$  is a vector in  $\mathbb{R}^n$  and  $x^+$  is the vector in  $\mathbb{R}^n$  with  $i$ -th component equal to  $(x_i)^+ = \max\{x_i, 0\}$ . In [7] was proposed a semi-smooth Newton's method for solving (1). Under suitable assumption

---

<sup>\*</sup>IME/UFG, Avenida Esperana, s/n Campus Samambaia, Goiânia, GO, 74690-900, Brazil (e-mail:numeroj@gmail.com). The author was supported in part by CAPES.

<sup>†</sup>IME/UFG, IME/UFG, Avenida Esperana, s/n Campus Samambaia, Goiânia, GO, 74690-900, Brazil (e-mail:yunier@ufg.br). The author was supported in part by FAPEG, CNPq Grants 303492/2013-9, 474160/2013-0 and PRONEX–Optimization(FAPERJ/CNPq).

<sup>‡</sup>IME/UFG, IME/UFG, Avenida Esperana, s/n Campus Samambaia, Goiânia, GO, 74690-900, Brazil (e-mail:orizon@ufg.br). The author was supported in part by FAPEG, CNPq Grants 4471815/2012-8, 305158/2014-7 and PRONEX–Optimization(FAPERJ/CNPq).

<sup>§</sup>School of Mathematics, The University of Birmingham, The Watson Building, Edgbaston, Birmingham B15 2TT, United Kingdom (e-mail:nemeths@for.mat.bham.ac.uk). The author was supported in part by the Hungarian Research Grant OTKA 60480.

was showed the finite convergence to a solution of (1). Some works dealing with (1) and its generalizations include [7–9, 12, 20, 39]. It is worth mentioning that a similar equation has been studied in [27].

The purpose of the present paper is to discuss the semi-smooth Newton’s method introduced in [7], to solve (1), under new assumptions. As an application, we use the obtained results to study the remarkable instance of (1),

$$[Q - \mathbf{I}]x^+ + x = -\tilde{b}, \quad (2)$$

where the data consists of  $Q$  a positive definite real matrix of size  $n \times n$  and  $\tilde{b} \in \mathbb{R}^n$ . Moreover, we present some computational experiments designed to investigate its practical viability. It is worth pointing out that the semi-smooth Newton’s method for solving (2) was studied in [17] and some computational tests were presented in [3]. The results obtained in this paper improve the ones of [17]. As we will show, the system (2) arises from the optimality condition of the convex quadratic programming problem under a positive constraint,

$$\begin{aligned} &\text{Minimize } \frac{1}{2}x^\top Qx + x^\top \tilde{b} + c \\ &\text{subject to } x \in \mathbb{R}_+^n, \end{aligned} \quad (3)$$

where  $c$  is a real number and  $\mathbb{R}_+^n$  is the nonnegative orthant. Note that, without loss of generality, we can assume  $Q$  symmetric in (3) because the objective function of (3) is equal to  $\frac{1}{2}x^\top \tilde{Q}x + x^\top \tilde{b} + c$ , where  $\tilde{Q} = \frac{1}{2}(Q + Q^\top)$  is a symmetric matrix. Positively constrained convex quadratic programming is equivalent to the problem of projecting the point onto a simplicial cone. The interest in the subject of projection arises in several situations, having a wide range of applications in pure and applied mathematics such as Convex Analysis (see *e.g.*, [21]), Optimization (see *e.g.*, [4, 10, 11, 37]), Numerical Linear Algebra (see *e.g.*, [38]), Statistics (see *e.g.*, [6, 15, 22]), Computer Graphics (see *e.g.*, [18]) and Ordered Vector Spaces (see *e.g.*, [1, 23, 24, 32, 33]). The projection onto a general simplicial cone is difficult and computationally expensive, this problem has been studied *e.g.*, in [2, 16, 19, 30, 31]. It is a special convex quadratic program and its KKT optimality conditions consists in a linear complementarity problem (LCP) associated with it, see *e.g.*, [29, 30]. Therefore, the problem of projecting onto simplicial cones can be solved by active set methods [5, 25, 26, 29] or any algorithms for solving LCPs, see *e.g.*, [5, 29] and special methods based on its geometry, see *e.g.*, [29, 30]. Other fashionable ways to solve this problem are based on the classical von Neumann algorithm (see *e.g.*, Dykstra algorithm [14, 15, 41]). Nevertheless, these methods are also quite expensive (see the numerical results in [28] and the remark preceding Section 6.3 in [40]).

Following the ideas of [27], we show that the approach using semi-smooth Newton’s method, for solving (3), has potential advantages over existing methods. The main advantage appears to be the global, linear convergence and to achieve accurate solutions of large scale problems in few iterations. Our numerical results suggest, for a given class of problem, that the number of required iterations is almost unchanged. The numerical results also indicate a remarkable robustness with respect to the starting point.

The organization of the paper is as follows. In Section 1.1, some notations and preliminaries used in the paper are presented. In Section 2 we study the convergence properties of the semi-smooth Newton’s method for solving (1). In Section 3 the results of Section 2 are applied to find a solution of (3). In Section 4 we present some computational tests. Some final remarks are made in Section 5.

## 1.1 Notations and preliminaries

In this subsection we present the notations and some auxiliary results used throughout the paper. Let  $\mathbb{R}^n$  be the  $n$ -dimensional Euclidean space with the canonical inner product  $\langle \cdot, \cdot \rangle$  and induced norm  $\|\cdot\|$ . The  $i$ -th component of a vector  $x \in \mathbb{R}^n$  is denoted by  $x_i$ . We use the partial ordering for vectors, defined by  $x \leq y$  meaning  $x_i \leq y_i$ , for all  $i = 1, \dots, n$ . For  $x \in \mathbb{R}^n$ ,  $\text{sgn}(x)$  will denote a vector with components equal to 1, 0 or  $-1$  depending on whether the corresponding component of the vector  $x$  is positive, zero or negative. If  $a \in \mathbb{R}$  and  $x \in \mathbb{R}^n$ , then denote  $a^+ := \max\{a, 0\}$ ,  $a^- := \max\{-a, 0\}$  and  $x^+$  and  $x^-$  the vectors with  $i$ -th component equal to  $(x_i)^+$  and  $(x_i)^-$ , respectively. From the definitions of  $x^+$  and  $x^-$  we have  $x = x^+ - x^-$ ,  $\langle x^+, x^- \rangle = 0$  and  $x^+, x^- \in \mathbb{R}_+^n$ .

**Lemma 1.** *Let  $x, y \in \mathbb{R}^n$ . Then  $\|y^+ - x^+ - \text{diag}(\text{sgn}(x^+))(y - x)\| \leq \|y - x\|$ .*

*Proof.* For each  $i \in \{1, \dots, n\}$ , we have two possibilities:

- (a)  $x_i < 0$ . In this case,  $\text{sgn}(x_i^+) = 0$ . Thus,  $|y_i^+ - x_i^+ - \text{sgn}(x_i^+)(y_i - x_i)| = |y_i^+| \leq |y_i - x_i|$ .
- (b)  $x_i \geq 0$ . In this case,  $\text{sgn}(x_i^+) = 1$ . Hence,  $|y_i^+ - x_i^+ - \text{sgn}(x_i^+)(y_i - x_i)| = |y_i^+ - y_i| \leq |y_i - x_i|$ .

Combining (a) and (b) we have  $(y_i^+ - x_i^+ - \text{sgn}(x_i^+)(y_i - x_i))^2 \leq (y_i - x_i)^2$ , for all  $i = 1, \dots, n$ , which implies the desired inequality.  $\square$

The matrix  $I \in \mathbb{R}^{n \times n}$  denotes the identity matrix. If  $x \in \mathbb{R}^n$  then  $\text{diag}(x) \in \mathbb{R}^{n \times n}$  will denote a diagonal matrix with  $(i, i)$ -th entry equal to  $x_i$ ,  $i = 1, \dots, n$ . Denote  $\|M\| := \max\{\|Mx\| : x \in \mathbb{R}^n, \|x\| = 1\}$  for any  $M \in \mathbb{R}^{n \times n}$ . The next useful result was proved in 2.1.1, page 32 of [34].

**Lemma 2.** *Let  $E \in \mathbb{R}^{n \times n}$ . If  $\|E\| < 1$ , then  $E - I$  is invertible and  $\|(E - I)^{-1}\| \leq 1/(1 - \|E\|)$ .*

We end this section with the contraction mapping principle (see 8.2.2, page 153 of [34]).

**Theorem 1** (contraction mapping principle). *Let  $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^n$ . Suppose that there exists  $\lambda \in [0, 1)$  such that  $\|\phi(y) - \phi(x)\| \leq \lambda\|y - x\|$ , for all  $x, y \in \mathbb{R}^n$ . Then there exists a unique  $\bar{x} \in \mathbb{R}^n$  such that  $\phi(\bar{x}) = \bar{x}$ .*

## 2 A semi-smooth Newton method for a piecewise linear systems

In this section we present and analyze the semi-smooth Newton's method for solving (1). We begin with an existence result of solution to the equation (1).

**Proposition 1.** *Let  $\lambda \in \mathbb{R}$ . If  $\|T^{-1}\| \leq \lambda < 1$  then (1) has unique solution for any  $b \in \mathbb{R}^n$ .*

*Proof.* The equation (1) has a solution if only if  $\phi(x) = -T^{-1}x^+ + T^{-1}b$  has a fixed point. It follows from definition of  $\phi$  that

$$\phi(y) - \phi(x) = -T^{-1}(y^+ - x^+), \quad x, y \in \mathbb{R}^n.$$

Since  $\|T^{-1}\| < \lambda < 1$ , the last equality implies that  $\|\phi(y) - \phi(x)\| \leq \lambda\|y - x\|$ , for all  $x, y \in \mathbb{R}^n$ . Hence  $\phi$  is a contraction. Therefore applying Theorem 1 we conclude that  $\phi$  has precisely a unique fixed point and consequently (1) has a unique solution.  $\square$

Then the assumption  $\|T^{-1}\| < 1$  in Proposition 1 is sufficient to the uniqueness of solution of (1). The next example shows that it is not possible to increase the upper bound of  $\|T^{-1}\|$  and still ensure the uniqueness of solution in (1).

**Example 1.** Consider the function  $F : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  defined by  $F(x) = x^+ + Tx - b$ , where

$$T = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ 2 \end{bmatrix}.$$

Note that  $\|T^{-1}\| = 1$  and there holds  $F(x^*) = F(x^{**}) = 0$ , where  $x^* = [1, 1]^T$  and  $x^{**} = [0, 1]^T$ .

The *semi-smooth Newton method* introduced in [36] for finding the zero of the function

$$F(x) := x^+ + Tx - b, \quad x \in \mathbb{R}^n, \quad (4)$$

with starting point  $x^0 \in \mathbb{R}^n$ , it is formally defined by

$$F(x^k) + V^k (x^{k+1} - x^k) = 0, \quad V^k \in \partial F(x^k), \quad k = 0, 1, \dots, \quad (5)$$

where  $V^k$  is any subgradient in  $\partial F(x^k)$  the Clarke generalized Jacobian of  $F$  at  $x^k$  (see Definition 2.6.1 on page 70 of [13]). Letting

$$P(x) := \text{diag}(\text{sgn}(x^+)), \quad x \in \mathbb{R}^n, \quad (6)$$

it easy to see that

$$P(x) + T \in \partial F(x), \quad x \in \mathbb{R}^n.$$

Since  $P(x)x = x^+$  for all  $x \in \mathbb{R}^n$ , taking  $V^k = P(x^k) + T$ , equation (5) becomes

$$\left[ P(x^k) + T \right] x^{k+1} = b, \quad k = 0, 1, \dots, \quad (7)$$

which define formally the *semi-smooth Newton sequence*  $\{x^k\}$  for solving (1). Note that the above iteration is exactly the one stated in equation (6) of [7]. We devote the rest of this section to studying the convergence properties of this sequence.

**Proposition 2.** Assume that the matrix  $P(x) + T$  is nonsingular for all  $x \in \mathbb{R}^n$ . Then,  $\{x^k\}$  is well defined and bounded from any starting point. Moreover, for each accumulation point  $\bar{x}$  of  $\{x^k\}$  there exists an  $\hat{x} \in \mathbb{R}^n$  such that

$$\left[ P(\hat{x}) + T \right] \bar{x} = b. \quad (8)$$

In particular, if  $\text{sgn}(\bar{x}^+) = \text{sgn}(\hat{x}^+)$ , then  $\bar{x}$  is a solution of (1).

*Proof.* To prove this result we follow similar arguments of Proposition 3 of [27]. □

The next proposition gives a condition for the Newton iteration (7) to finish in a finite number of steps, which can be proved by using the same argument as the one used in the proof of Lemma 3 of [7].

**Proposition 3.** If in (7) it happens that  $\text{sgn}((x^{k+1})^+) = \text{sgn}((x^k)^+)$ , then  $x^{k+1}$  is a solution of (1).

Next, we state and prove a theorem for the semi-smooth Newton's method (7) for solving (1).

**Theorem 2.** Let  $b \in \mathbb{R}^n$  and  $T \in \mathbb{R}^{n \times n}$  be a nonsingular matrix. Assume that  $\|T^{-1}\| < 1$ . Then, for any starting point  $x^0 \in \mathbb{R}^n$ ,  $\{x^k\}$  is well-defined. Additionally, if

$$\|T^{-1}\| < 1/2, \quad (9)$$

then  $\{x^k\}$  converges Q-linearly to  $x^* \in \mathbb{R}^n$ , the unique solution of (1), as follows

$$\|x^* - x^{k+1}\| \leq \frac{\|T^{-1}\|}{1 - \|T^{-1}\|} \|x^* - x^k\|, \quad k = 0, 1, \dots \quad (10)$$

*Proof.* Let  $x \in \mathbb{R}^n$ . Since  $\|T^{-1}\| < 1$ , the definition of  $P(x)$  implies  $\|T^{-1}P(x)\| \leq \|T^{-1}\| < 1$ . Thus, Lemma 2 implies that  $-T^{-1}P(x) - \mathbf{I}$  is nonsingular. Because  $T$  is nonsingular and

$$P(x) + T = -T [-T^{-1}P(x) - \mathbf{I}], \quad x \in \mathbb{R}^n,$$

we conclude that  $P(x) + T$  is also nonsingular. Hence, for any starting point  $x^0 \in \mathbb{R}^n$ , (7) implies that  $\{x^k\}$  is well-defined.

Using Proposition 1, we conclude that (1) has a unique solution  $x^* \in \mathbb{R}^n$ . Since  $x^* \in \mathbb{R}^n$  is the solution of (1), we have  $[P(x^*) + T]x^* - b = 0$ , which together with definition of  $\{x^k\}$  in (7) and (6) implies

$$x^* - x^{k+1} = -[P(x^k) + T]^{-1} [[P(x^*) + T]x^* - b - [P(x^k) + T]x^k + b - [P(x^k) + T](x^* - x^k)], \quad k = 0, 1, \dots$$

On the other hand, since  $P(x)x = x^+$  for all  $x \in \mathbb{R}^n$ , after simple algebraic manipulations we obtain

$$[P(x^*) + T]x^* - b - [P(x^k) + T]x^k + b - [P(x^k) + T](x^* - x^k) = (x^*)^+ - (x^k)^+ - P(x^k)(x^* - x^k),$$

for  $k = 0, 1, \dots$ . Combining the two above equalities and using properties of the norm we have

$$\|x^* - x^{k+1}\| \leq \left\| [P(x^k) + T]^{-1} \right\| \left\| (x^*)^+ - (x^k)^+ - P(x^k)(x^* - x^k) \right\|, \quad k = 0, 1, \dots$$

It follows from Lemma 1 that  $\left\| (x^*)^+ - (x^k)^+ - P(x^k)(x^* - x^k) \right\| \leq \|x^* - x^k\|$ , for  $k = 0, 1, \dots$ , and the last inequality becomes

$$\|x^* - x^{k+1}\| \leq \left\| [P(x^k) + T]^{-1} \right\| \|x^* - x^k\|, \quad k = 0, 1, \dots \quad (11)$$

On the other hand, after some algebra and using properties of the norm, we have

$$\left\| [P(x^k) + T]^{-1} \right\| = \left\| [-T^{-1}P(x^k) - \mathbf{I}]^{-1} [-T^{-1}] \right\| \leq \left\| [T^{-1}P(x^k) + \mathbf{I}]^{-1} \right\| \|T^{-1}\|, \quad k = 0, 1, \dots,$$

which combined with Lemma 2 and considering that  $\|T^{-1}P(x^k)\| \leq \|T^{-1}\| < 1$ , implies

$$\left\| [P(x^k) + T]^{-1} \right\| \leq \frac{\|T^{-1}\|}{1 - \|T^{-1}\|}, \quad k = 0, 1, \dots$$

Thus, last inequality together with (11) gives (10). Assumption (9) implies  $\|T^{-1}\|/(1 - \|T^{-1}\|) < 1$ . Therefore, (10) implies that  $\{x^k\}$  converges Q-linearly, from any starting point  $x^0$ , to the solution  $x^*$  of (1). Hence the theorem is proven.  $\square$

For stating the next result we need the following definition. Let  $S := (s_{ij}) \in \mathbb{R}^{n \times n}$  be with  $i$ -th row  $s_i := (s_{i1}, \dots, s_{in})^T$ ,  $i = 1, \dots, n$ . We say that  $S$  has , if for each  $i$ -th row  $s_i$  either  $s_i \geq 0$  or  $s_i \leq 0$ .

**Example 2.** The following three matrices have its rows with definite sign:

$$\begin{bmatrix} -2 & -3 & -1 \\ 1 & 1 & 2 \\ 5 & 2 & 1 \end{bmatrix}, \quad \begin{bmatrix} 2 & 3 & 1 \\ 1 & 1 & 2 \\ 5 & 2 & 1 \end{bmatrix}, \quad \begin{bmatrix} -2 & -3 & -1 \\ -1 & -1 & -2 \\ -5 & -2 & -1 \end{bmatrix}.$$

**Example 3.** It follows from [35, Theorem 2] that, if  $A \in \mathbb{R}^{n \times n}$  is a non-singular  $M$ -matrix then  $(A + D)^{-1} \geq 0$ , for each diagonal matrix  $D \in \mathbb{R}^{n \times n}$  with  $D \geq 0$ . In particular, if  $A \in \mathbb{R}^{n \times n}$  is an  $M$ -matrix, then  $(A + D)^{-1}$  has its rows with definite sign, for each  $D \geq 0$ .

**Theorem 3.** Assume that (1) has solutions. If  $[P(x) + T]^{-1}$  exists and have its rows with definite sign, for all  $x \in \mathbb{R}^n$ . Then  $\{x^k\}$  generated by (7) converges after finite steps for the unique solution of (1).

*Proof.* First of all note that the sequence generated by (7) satisfies

$$F(x^k) + [P(x^k) + T](x^{k+1} - x^k) = 0, \quad k = 0, 1, \dots, \quad (12)$$

where the function  $F$  is defined in (4). By direct computation, we have

$$F(y) - F(x) - [P(x) + T](y - x) = P(y)y - P(x)y \geq 0, \quad x, y \in \mathbb{R}^n. \quad (13)$$

For arbitrary  $x^0 \in \mathbb{R}^n$ , the above inequality and (12) imply that

$$F(x^1) \geq F(x^0) + [P(x^0) + T](x^1 - x^0) = 0.$$

Thus, applying an induction argument we conclude that

$$F(x^k) = [P(x^k) + T]x^k - b \geq 0, \quad k = 1, 2, \dots \quad (14)$$

Let  $x^*$  be a solution of (1). Letting  $y = x^*$  and  $x = x^k$  in (13), we obtain

$$0 = F(x^*) \geq F(x^k) + [P(x^k) + T](x^* - x^k). \quad (15)$$

Since  $s_i = (s_{i1}, \dots, s_{in})^T$ , the  $i$ -th row of  $[P(x) + T]^{-1} =: (s_{ij})$ , has all elements either non-negative or non-positive, we have only two options:  $\text{sgn}(s_i^T)$  has its components equal to  $-1$  or  $0$ , or  $\text{sgn}(s_i^T)$  has its components equal  $0$  or  $1$ . Multiplying both sides of (15) by  $[P(x^k) + T]^{-1}$  and using (14), we have

$$x_i^* \leq x_i^k - s_i F(x^k) \leq x_i^k, \quad i \in I_+ := \{1 \leq i \leq n : \text{sgn}(s_i^T) \in \{0, 1\}\}, \quad (16)$$

for all  $k \geq 1$ , and similarly

$$x_i^* \geq x_i^k - s_i F(x^k) \geq x_i^k, \quad i \in I_- := \{1 \leq i \leq n : \text{sgn}(s_i^T) \in \{-1, 0\}\}. \quad (17)$$

Note that as  $[T + P(x^k)]^{-1}$  exists, then there are no indexes  $i$  and  $j$  such that  $s_i = s_j$ , thus  $I_+ \cap I_- = \emptyset$  and  $I_+ \cup I_- = \{1, 2, \dots, n\}$ . It follows from (5), (7) and  $V^k = P(x^k) + T$  that

$$x^{k+1} = [T + P(x^k)]^{-1}b = x^k - [P(x^k) + T]^{-1}F(x^k), \quad k = 0, 1, \dots$$

Therefore, using (14) and the definition of  $I_+$ , we obtain

$$x_i^* \leq x_i^{k+1} \leq x_i^k, \quad i \in I_+, \quad (18)$$

where the first inequality above follows from (16), and analogously using (17), we have

$$x_i^* \geq x_i^{k+1} \geq x_i^k, \quad i \in I_-. \quad (19)$$

Hence,  $\{x^k\}$  converges, because  $\{x_i^k\}$  is monotone and bounded by  $x_i^*$  for  $i = 1, \dots, n$ . Thus,  $\{x_i^k\}$  has a limit  $u_i$ . Therefore,  $\{x^k\}$  converges to the vector  $u$  with components  $u_i$ . By using again (12), we have

$$\|F(u)\| = \lim_{k \rightarrow \infty} \|F(x^k)\| = \lim_{k \rightarrow \infty} \|[P(x^k) + T](x^{k+1} - x^k)\| \leq (1 + \|T\|) \lim_{k \rightarrow \infty} \|x^{k+1} - x^k\| = 0.$$

Therefore,  $u$  is a solution. Furthermore, for any two solutions  $x^*$  and  $y^*$ , (13) implies

$$0 = F(x^*) - F(y^*) \geq [T + P(y^*)](x^* - y^*). \quad (20)$$

Then, multiplying by  $[T + P(y^*)]^{-1}$  we obtain

$$y_i^* \geq x_i^* \quad i \in I_+ \quad \text{and} \quad y_i^* \leq x_i^* \quad i \in I_-.$$

The result follows by reversing the roles of  $x^*$  and  $y^*$  in (20). Thus, the problem has a unique solution equal to the limit of the sequence  $\{x^k\}$  generated by (7).

Finally we establish the finite termination of the sequence  $\{x^k\}$  at the unique solution of problem (1), which will be denoted by  $x^*$ . Since for all  $x \in \mathbb{R}^n$   $P(x)$  has at most  $2^n$  different choices, then there exist  $j, \ell \in \mathbb{N}$  with  $1 \leq \ell < 2^n$  such that  $P(x^j) = P(x^{j+\ell})$ . Note that if  $\ell = 1$ , then Proposition 3 implies that  $x^{j+2}$  is solution of (1). This statement implies that

$$x^{j+1} = [T + P(x^j)]^{-1}b = [T + P(x^{j+\ell})]^{-1}b = x^{j+\ell+1}.$$

Applying inductively this argument,

$$x^{j+1} = x^{j+\ell+1}, \quad x^{j+2} = x^{j+\ell+2}, \quad \dots, \quad x^{j+\ell} = x^{j+2\ell}, \quad x^{j+\ell+1} = x^{j+2\ell+1} = x^{j+1}.$$

Thus, the sequence  $\{x^k\}$  generated by (7) has at most  $j + \ell$  different elements. Now using (18) and (19), we obtain

$$x_i^{j+1} \geq x_i^{j+2} \geq \dots \geq x_i^{j+\ell+1} = x_i^{j+1}, \quad i \in I_+,$$

and

$$x_i^{j+1} \leq x_i^{j+2} \leq \dots \leq x_i^{j+\ell+1} = x_i^{j+1}, \quad i \in I_-.$$

Hence,  $x^{j+1} = x^{j+2}$  and in view Proposition 3 we conclude that  $x^{j+2}$  is solution of (1), i.e.,  $x^{j+2} = x^*$ .  $\square$

It is worth mentioning that Theorem 3 generalizes Theorem 2 of [7], in the special case  $[P(x) + T]^{-1} \geq 0$ , for all  $x \in \mathbb{R}^n$ . The invertibility of  $P(x) + T$ , for all  $x \in \mathbb{R}^n$ , is sufficient to the well-definedness of the semi-smooth Newton method. However, the next example show that, for the convergence of these methods, an additional condition on  $T$  must be assumed, for instance, (9) or  $[P(x) + T]^{-1}$  exists with its rows having definite sign, for all  $x \in \mathbb{R}^n$ .

**Example 4.** Consider the function  $F : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  defined by  $F(x) = x^+ + Tx - b$ , where

$$T = \begin{bmatrix} -2 & 3 \\ -1 & 1 \end{bmatrix}, \quad b = \begin{bmatrix} -5 \\ -3 \end{bmatrix}.$$

Note that  $\|T^{-1}\| = 3,86\dots$ , the matrix  $P(x) + T$  is invertible and have no rows with definite sign, for all  $x \in \mathbb{R}^2$ . Moreover,  $F$  has  $x^* = [2, -1]^T$  as the unique zero. Applying semi-smooth Newton method starting with  $x^0 = [-3, 3]^T$ , for finding the zero of  $F$ , the generated sequence oscillates between the points

$$x^1 = \begin{bmatrix} 4 \\ 1 \end{bmatrix}, \quad x^2 = \begin{bmatrix} -1 \\ -2 \end{bmatrix}.$$



### 3 Application to quadratic programming

In this section, we apply the results of Section 2 to solve (2), in order to find a solution of (3). We begin showing that, from each solution of (2) we obtain a solution of (3). From now on we assume that  $Q$  is a symmetric and positive definite matrix.

**Proposition 4.** *If the vector  $x^*$  is a solution of (2), then  $(x^*)^+$  is a solution of (3).*

*Proof.* The optimality conditions of the problem in (3) are given by

$$x \in \mathbb{R}_+^n, \quad Qx + \tilde{b} \in \mathbb{R}_+^n, \quad \langle Qx + \tilde{b}, x \rangle = 0. \quad (21)$$

We claim that  $(x^*)^+$  is a solution of (21). We know that  $(x^*)^+ - x^* = (x^*)^-$ . Thus, if  $x^* \in \mathbb{R}^n$  is a solution of (2), then

$$Q(x^*)^+ + \tilde{b} = (x^*)^-.$$

Hence, by using  $(x^*)^- \in \mathbb{R}_+^n$  and  $\langle (x^*)^-, (x^*)^+ \rangle = 0$ , the last equality easily implies that

$$Q(x^*)^+ + \tilde{b} \in \mathbb{R}_+^n, \quad \langle Q(x^*)^+ + \tilde{b}, (x^*)^+ \rangle = 0.$$

Combining this with  $(x^*)^+ \in \mathbb{R}_+^n$ , we conclude that  $(x^*)^+$  is a solution of (21) as claimed, which completes the proof.  $\square$

The *semi-smooth Newton method* for solving (2), with starting point  $x^0 \in \mathbb{R}^n$ , is given by

$$x^{k+1} = - \left( [Q - I] P(x^k) + I \right)^{-1} \tilde{b}, \quad k = 0, 1, \dots \quad (22)$$

**Remark 1.** *If  $Q - I$  is a nonsingular matrix,  $T = [Q - I]^{-1}$  and  $b = -T\tilde{b}$ , then (2) and (1) are equivalent. Moreover, (22) becomes*

$$x^{k+1} = \left[ T^{-1} P(x^k) + I \right]^{-1} T^{-1} b = \left[ P(x^k) + T \right]^{-1} b, \quad k = 0, 1, \dots,$$

*which is the semi-smooth Newton method defined in (7).*

**Proposition 5.** *Let  $\lambda \in \mathbb{R}$ . If  $\|Q - I\| \leq \lambda < 1$  then (2) has a unique solution.*

*Proof.* The proof follows by combining Remark 1 with Proposition 1.  $\square$

The next result shows that the semi-smooth Newton defined in (22) is always well defined.

**Lemma 3.** *Let  $x \in \mathbb{R}^n$ . The following matrix is nonsingular*

$$[Q - I] P(x) + I. \quad (23)$$

*As a consequence, the semi-smooth Newton sequence  $\{x^k\}$  is well-defined, for any starting point  $x^0 \in \mathbb{R}^n$ .*

*Proof.* The proof of the first part of the lemma, follows similar argument to the proof of Lemma 5 of [17]. To prove the second part of the lemma, combine the definition of  $\{x^k\}$  in (22) and the first part of the lemma.  $\square$

**Proposition 6.** *If in (22) it happens that  $\text{sgn}((x^{k+1})^+) = \text{sgn}((x^k)^+)$ , then  $x^{k+1}$  is a solution of (2).*

*Proof.* The proof follows combining Remark 1 and Proposition 3. □

**Proposition 7.** *The sequence  $\{x^k\}$ , defined in (22), is bounded from any starting point. Moreover, for each accumulation point  $\bar{x}$  of  $\{x^k\}$ , there exists an  $\hat{x} \in \mathbb{R}^n$  such that*

$$([Q - I]P(\hat{x}) + I)\bar{x} = -\tilde{b}. \quad (24)$$

*In particular, if  $\text{sgn}(\bar{x}^+) = \text{sgn}(\hat{x}^+)$  then  $\bar{x}$  is a solution of (2).*

*Proof.* Using Remark 1 and Proposition 2 the result follows. □

**Theorem 4.** *The sequences  $\{x^k\}$  generated by the semi-smooth Newton Method (22) for solving (2), is well defined for any starting point  $x^0 \in \mathbb{R}^n$ . Moreover, if*

$$\|Q - I\| < 1/2, \quad (25)$$

*then the sequence  $\{x^k\}$  converges  $Q$ -linearly to  $x^* \in \mathbb{R}^n$ , the unique solution of (2), as follows*

$$\|x^* - x^{k+1}\| \leq \frac{\|Q - I\|}{1 - \|Q - I\|} \|x^* - x^k\|, \quad k = 0, 1, \dots, \quad (26)$$

*and  $(x^*)^+$  is a solution of (3).*

*Proof.* The well-definedness, for any starting point  $x^0 \in \mathbb{R}^n$ , follows from Lemma 3. For concluding the proof combine, Proposition 4, Remark 1 and Theorem 2. □

Note that (25) implies that the eigenvalues of  $Q$  belong to  $(0, \frac{1}{2}) \cup (\frac{1}{2}, \frac{3}{2})$ . Let us present an important equivalent form of problem (3).

**Example 5.** *Given  $A \in \mathbb{R}^{n \times n}$  a nonsingular matrix,  $A\mathbb{R}_+^n := \{Ax : x \in \mathbb{R}_+^n\}$  and  $z \in \mathbb{R}^n$ . The projection  $P_{A\mathbb{R}_+^n}(z)$  of the point  $z$  onto the cone  $A\mathbb{R}_+^n$  is defined by*

$$P_{A\mathbb{R}_+^n}(z) := \operatorname{argmin} \left\{ \frac{1}{2} \|z - y\|^2 : y \in A\mathbb{R}_+^n \right\}.$$

*From the definition of the simplicial cone associated with the matrix  $A$ , the problem of projecting the point  $z \in \mathbb{R}^n$  onto a simplicial cone  $A\mathbb{R}_+^n$  may be stated as the following positively constrained quadratic programming problem*

$$\begin{aligned} & \text{Minimize } \frac{1}{2} \|z - Ax\|^2, \\ & \text{subject to } x \in \mathbb{R}_+^n. \end{aligned}$$

*Hence, if  $v \in \mathbb{R}^n$  is the unique solution of this problem then we have  $P_{A\mathbb{R}_+^n}(z) = Av$ . The above problem is equivalent to the following nonnegatively constrained quadratic programming problem*

$$\begin{aligned} & \text{Minimize } \frac{1}{2} x^\top Qx + x^\top \tilde{b} + c \\ & \text{subject to } x \in \mathbb{R}_+^n, \end{aligned} \quad (27)$$

*by taking  $Q = A^\top A$ ,  $\tilde{b} = -A^\top z$  and  $c = z^\top z/2$ . The optimality condition for problem (27) implies that its solution can be obtained by solving the following linear complementarity problem*

$$y - Qx = \tilde{b}, \quad x \geq 0, \quad y \geq 0, \quad \langle x, y \rangle = 0. \quad (28)$$

**Remark 2.** *It is easy to establish that corresponding to each nonnegative quadratic problems (27) and each linear complementarity problems (28) associated to positive definite matrices, there are equivalent problems of projection onto simplicial cones. Therefore, the problem of projecting onto simplicial cones can be solved by active set methods [5, 25, 26, 29] or any algorithms for solving LCPs, see e.g., [5, 29] and special methods based on its geometry, see e.g., [29, 30]. Other fashionable ways to solve this problem are based on the classical von Neumann algorithm (see e.g., the Dykstra algorithm [14, 15, 41]). Nevertheless, these methods are also quite expensive (see the numerical results in [28] and the remark preceding section 6.3 in [40])*

## 4 Computational results

In this section we test our semi-smooth Newton method (22) to find solutions on generated random instances of (2). We present two types of experiments. In one of them, we guarantee that for each test problem the hypotheses given in Theorem 4 are satisfied and in the other they are not.

All programs were implemented in MATLAB Version 7.11 64-bit and run on a 3.40GHz Intel Core i5 – 4670 with 8.0GB of RAM. All MATLAB codes and generated data of this paper are available in <http://orizon.mat.ufg.br/pages/34449-publications>.

All experiments are based on the following general considerations:

- In order to accurately measure the method’s runtime for a problem, each one of the test problems was solved 10 times and the runtime data collected. Then, we defined the corresponding *method’s runtime for a problem* as the median of these measurements.
- Let  $\text{Tol } X \in \mathbb{R}_+$  be a relative bound, we consider that the method converged to the solution and stopped the execution when, for some  $k$ , the condition

$$\|u - x^k\| < \text{Tol } X(1 + \|u\|),$$

is satisfied. If the previous stopping criteria are not met within 100 iterations, we declare that the method did not converge.

### 4.1 When the hypotheses of Theorem 4 are satisfied

In this experiment, we studied the behavior of the method on sets of 100 randomly generated test problems of dimension  $n = 2000, 3000, 4000, 5000$ , respectively. Furthermore, we analyzed the influence of the initial point in the convergence of the method on 1000 randomly generated test problems of dimension  $n = 100$ . For each test problem in this experiment the hypotheses given in the Theorem 4 are satisfied, generating each of them as follows:

1. To construct the matrix  $Q \in \mathbb{R}^{n \times n}$  symmetric and positive definite satisfying the assumption (25) in Theorem 4, we first chose a random number  $\beta$  from the standard uniform distribution on the open interval  $(0, 1/2)$ . Secondly, we compute the singular value decomposition  $U\Sigma V^T$  of a symmetric and positive definite matrix of the form  $B^T B$ , where  $B$  is a generated  $n \times n$  real nonsingular matrix containing random values drawn from the uniform distribution on the interval  $[-10^6, 10^6]$ . Finally, in the present case the equality  $V = U$  holds and we compute the matrix  $Q$  from

$$Q = U \left( I + \frac{\beta}{\sigma} \Sigma \right) U^T,$$

where  $\sigma$  is the largest singular value of  $\Sigma$ . It is important to note that by construction of the matrix  $Q$  always  $\beta = \|Q - I\|$ .

2. We have chosen the solution  $u \in \mathbb{R}^n$  containing random values drawn from the uniform distribution on the interval  $[-10^6, 10^6]$  and then we have computed  $\tilde{b} \in \mathbb{R}^n$  from equation (2).
3. Finally we have chosen a starting point  $x^0 \in \mathbb{R}^n$  containing random values drawn from the uniform distribution on the interval  $[-10^6, 10^6]$ .

In accordance with the theoretical convergence of the method, ensured by Theorem 4, the computational convergence is obtained in all cases.

The computational results to analyze the behavior of the method on sets of 100 generated random test problems of different dimensions, are reported in Table 1. From these, it can be noted that for the same dimension, to achieve higher accuracy, the method does not experience a significant increase in the number of iterations or in runtime. On the other hand, the increase in the dimension of the problems does not necessarily involve an increase in the number of iterations to achieve the same accuracy, however, a larger runtime is consumed. A larger runtime consumption is associated with the fact that the semi-smooth Newton method (22) requires the solution of a linear system in each iteration, whose computational effort increases with the dimension of the problem. Another important aspect that can be checked in Table 1 is the ability of the method to converge in about three iterations on average.

$n$	Total Iterations			Total Time		
2000	278	294	296	142.48	147.77	148.05
3000	282	295	299	445.61	465.48	471.65
4000	278	297	300	1013.79	1082.43	1093.55
5000	285	303	307	1945.23	2067.08	2112.72
Tol $X$	$10^{-6}$	$10^{-8}$	$10^{-10}$	$10^{-6}$	$10^{-8}$	$10^{-10}$

Table 1: Total overall iterations and total time in seconds, performed and consumed, respectively by the semi-smooth Newton method (22) to solve the 100 test problems of each dimension for different accuracies.

In order to study the influence of the initial point in the convergence of the method, we have generated 1000 test problems of dimension  $n = 100$  and we have associated to each of them 1000 generated initial points. We have solved each problem with the 1000 corresponding initial points. Then, we have computed the standard deviation (STD)  $\bar{d}_i$  and the mean value (MEAN)  $\bar{m}_i$  of the number of iterations performed by the method to solve the problem  $i$  taking each one of the 1000 initial points. Finally we have computed the mean of all  $\bar{d}_i$  and the mean of all  $\bar{m}_i$ ,  $i = 1, \dots, 1000$ . All cases converged, indicating robustness of the method with respect to the starting point. The results are shown in Table 2. The standard deviation of the number of iterations performed by the method to solve the problem  $i$  with the 1000 initial points gives us an idea of the influence of the initial point in the number of iterations performed by the method in each problem. The reported means of these standard deviation values give us an idea of the influence of the initial point in the number of iterations performed by the method in all the problems in general. The results in the table show that on average the number of iterations performed by our method to find the solution for a problem varies only very slightly with the chosen starting point. Again we see that the average number of iterations performed is less than three.

Tol X	MEAN ( $\{\bar{d}_i\}_{i=1,\dots,1000}$ )	MEAN ( $\{\bar{m}_i\}_{i=1,\dots,1000}$ )
$10^{-6}$	0.2450	2.3331
$10^{-8}$	0.2530	2.3454
$10^{-10}$	0.2536	2.3457

Table 2: Influence of the initial point in the convergence of the semi-smooth Newton method (22) on a total of 1000 test problems of dimension  $n = 100$  each of them with 1000 generated initial points for different accuracies.

## 4.2 When the hypotheses of Theorem 4 are not satisfied

In this experiment, we studied the behavior of the method on 1000 test problems of dimension  $n = 1000$ , where the hypotheses given in the Theorem 4 are not all satisfied.

In this case, the test problems were built almost as in the previous experiment. The only difference was in the construction of the matrix  $Q \in \mathbb{R}^{n \times n}$  not satisfying the assumption (25) of Theorem 4. Namely, we chose the random number  $\beta$  from the standard uniform distribution on the interval  $[lb, ub)$ , where  $\frac{1}{2} \leq lb < ub$ .

According to the obtained numerical results, we can conjecture that our method converges to a much broader class of problems, not satisfying the hypotheses of Theorem 4. However we detected that convergence with high accuracy to the solution largely depends on the magnitude of the value of the norm in condition (25). This idea can be observed inspecting Table 3. As the magnitude of the value of the norm in (25) increases sufficiently, the number of problems for which the method converges to the solution with greater accuracy decreases. This phenomenon, of course, is not associated to the convergence of the method for a specific problem, but, rather, there is an optimum accuracy achievable due to the accumulated errors. Small tolerances do not ensure obtaining accurate results. It can be the case that convergence is overlooked and unnecessary iterations are performed. It is important to note in the table that, even when the hypothesis is unfulfilled, the method converges for these problems, however it can be noted that the number of iterations performed by the method increases with respect of the previous experiments in which the hypotheses were fulfilled.

$\beta \in [lb, ub)$	Solved Problems			Iterations		
$[0.5, 10^3)$	1000	1000	1000	7.2160	7.2190	7.2190
$[10^3, 10^4)$	1000	1000	1000	9.1800	9.1850	9.1850
$[10^4, 10^5)$	1000	1000	1000	9.6730	9.6760	9.6760
$[10^5, 10^6)$	1000	1000	693	10.2820	10.2860	10.2540
$[10^6, 10^7)$	1000	999	0	10.3870	10.3874	-
$[10^7, 10^8)$	998	690	0	10.4339	10.4246	-
Tol X	$10^{-6}$	$10^{-8}$	$10^{-10}$	$10^{-6}$	$10^{-8}$	$10^{-10}$

Table 3: Number of problems solved by the semi-smooth Newton method (22) on a total of 1000 test problems of dimension  $n = 1000$  of each condition ( $lb \leq \beta < ub$ ) for different accuracies, and the mean number of iterations performed by the semi-smooth Newton method (22) to solve one problem in each case.

## 5 Conclusions

In this paper we studied a special class of convex quadratic programming under positive constraint, which, via its optimality conditions, is reduced to finding the unique solution of a nonsmooth system of equations. Our main result shows that, under a mild assumption on the simplicial cone, we can apply a semi-smooth Newton method for finding a unique solution of the obtained associated nonsmooth system of equations and that the generated sequence converges linearly to the solution for any starting point. It would be interesting to see whether the used technique can be applied for solving more general convex programs.

Since the optimality condition of a positive constrained convex quadratic programming problem is equivalent to a linear complementarity problem, which is equivalent to the problem of finding the unique solution of a nonsmooth system of equations, another interesting problem to address is to compare our semi-smooth Newton method with active set methods [5, 25, 26, 29].

This paper is a continuation of [17], where we studied the problem of projection onto a simplicial cone by using a semi-smooth Newton method. We expect that the results of this paper become a further step towards solving general convex optimization problems. We foresee further progress in this topic in the near future.

## References

- [1] M. Abbas and S. Z. Németh. Solving nonlinear complementarity problems by isotonicity of the metric projection. *J. Math. Anal. Appl.*, 386(2):882–893, 2012.
- [2] K. S. Al-Sultan and K. G. Murty. Exterior point algorithms for nearest points and convex quadratic programs. *Math. Programming*, 57(2, Ser. B):145–161, 1992.
- [3] J. Barrios, O. P. Ferreira, and S. Z. Németh. Projection onto simplicial cones by Picard’s method. *Linear Algebra Appl.*, 480:27–43, 2015.
- [4] H. H. Bauschke and J. M. Borwein. On projection algorithms for solving convex feasibility problems. *SIAM Rev.*, 38(3):367–426, 1996.
- [5] M. S. Bazaraa, H. D. Sherali, and C. M. Shetty. *Nonlinear programming*. Wiley-Interscience [John Wiley & Sons], Hoboken, NJ, third edition, 2006. Theory and algorithms.
- [6] R. Berk and R. Marcus. Dual cones, dual norms, and simultaneous inference for partially ordered means. *J. Amer. Statist. Assoc.*, 91(433):318–328, 1996.
- [7] L. Brugnano and V. Casulli. Iterative solution of piecewise linear systems. *SIAM J. Sci. Comput.*, 30(1):463–472, 2007/08.
- [8] L. Brugnano and V. Casulli. Iterative solution of piecewise linear systems and applications to flows in porous media. *SIAM J. Sci. Comput.*, 31(3):1858–1873, 2009.
- [9] L. Brugnano and A. Sestini. Iterative solution of piecewise linear systems for the numerical solution of obstacle problems. *JNAIAM. J. Numer. Anal. Ind. Appl. Math.*, 6(3-4):67–82 (2012), 2011.
- [10] Y. Censor, T. Elfving, G. T. Herman, and T. Nikazad. On diagonally relaxed orthogonal projection methods. *SIAM J. Sci. Comput.*, 30(1):473–504, 2007/08.

- [11] Y. Censor, D. Gordon, and R. Gordon. Component averaging: an efficient iterative parallel algorithm for large and sparse unstructured problems. *Parallel Comput.*, 27(6):777–808, 2001.
- [12] J. Chen and R. P. Agarwal. On Newton-type approach for piecewise linear systems. *Linear Algebra Appl.*, 433(7):1463–1471, 2010.
- [13] F. H. Clarke. *Optimization and nonsmooth analysis*, volume 5 of *Classics in Applied Mathematics*. Society for Industrial and Applied Mathematics (SIAM), Philadelphia, PA, second edition, 1990.
- [14] F. Deutsch and H. Hundal. The rate of convergence of Dykstra’s cyclic projections algorithm: the polyhedral case. *Numer. Funct. Anal. Optim.*, 15(5-6):537–565, 1994.
- [15] R. L. Dykstra. An algorithm for restricted least squares regression. *J. Amer. Statist. Assoc.*, 78(384):837–842, 1983.
- [16] A. Ekárt, A. B. Németh, and S. Z. Németh. Rapid heuristic projection on simplicial cones, 2010.
- [17] O. P. Ferreira and S. Z. Németh. Projection onto simplicial cones by a semi-smooth Newton method. *Optim. Lett.*, 9(4):731–741, 2015.
- [18] J. D. Foley, A. van Dam, S. K. Feiner, and J. F. Hughes. *Computer Graphics: Principles and Practice*. Addison-Wesley systems programming series, 1990.
- [19] H. Frick. Computing projections into cones generated by a matrix. *Biometrical J.*, 39(8):975–987, 1997.
- [20] A. Griewank, J.-U. Bernt, M. Radons, and T. Streubel. Solving piecewise linear systems in abs-normal form. *Linear Algebra Appl.*, 471:500–530, 2015.
- [21] J.-B. Hiriart-Urruty and C. Lemaréchal. *Convex analysis and minimization algorithms: Fundamentals. I*, volume 305 of *Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences]*. Springer-Verlag, Berlin, 1993.
- [22] X. Hu. An exact algorithm for projection onto a polyhedral cone. *Aust. N. Z. J. Stat.*, 40(2):165–170, 1998.
- [23] G. Isac and A. B. Németh. Monotonicity of metric projections onto positive cones of ordered Euclidean spaces. *Arch. Math. (Basel)*, 46(6):568–576, 1986.
- [24] G. Isac and A. B. Németh. Isotone projection cones in Euclidean spaces. *Ann. Sci. Math. Québec*, 16(1):35–52, 1992.
- [25] Z. Liu and Y. Fathi. An active index algorithm for the nearest point problem in a polyhedral cone. *Comput. Optim. Appl.*, 49(3):435–456, 2011.
- [26] Z. Liu and Y. Fathi. The nearest point problem in a polyhedral set and its extensions. *Comput. Optim. Appl.*, 53(1):115–130, 2012.
- [27] O. L. Mangasarian. A generalized Newton method for absolute value equations. *Optim. Lett.*, 3(1):101–108, 2009.

- [28] P. M. Morillas. Dykstra’s algorithm with strategies for projecting onto certain polyhedral cones. *Appl. Math. Comput.*, 167(1):635–649, 2005.
- [29] K. G. Murty. *Linear complementarity, linear and nonlinear programming*, volume 3 of *Sigma Series in Applied Mathematics*. Heldermann Verlag, Berlin, 1988.
- [30] K. G. Murty and Y. Fathi. A critical index algorithm for nearest point problems on simplicial cones. *Math. Programming*, 23(2):206–215, 1982.
- [31] A. B. Németh and S. Z. Németh. How to project onto an isotone projection cone. *Linear Algebra Appl.*, 433(1):41–51, 2010.
- [32] S. Z. Németh. Characterization of latticial cones in Hilbert spaces by isotonicity and generalized infimum. *Acta Math. Hungar.*, 127(4):376–390, 2010.
- [33] S. Z. Németh. Isotone retraction cones in Hilbert spaces. *Nonlinear Anal.*, 73(2):495–499, 2010.
- [34] J. M. Ortega. *Numerical analysis*, volume 3 of *Classics in Applied Mathematics*. Society for Industrial and Applied Mathematics (SIAM), Philadelphia, PA, second edition, 1990. A second course.
- [35] R. J. Plemmons.  $M$ -matrix characterizations. I. Nonsingular  $M$ -matrices. *Linear Algebra and Appl.*, 18(2):175–188, 1977.
- [36] L. Q. Qi and J. Sun. A nonsmooth version of Newton’s method. *Math. Programming*, 58(3, Ser. A):353–367, 1993.
- [37] H. D. Scolnik, N. Echebest, M. T. Guardarucci, and M. C. Vacchino. Incomplete oblique projections for solving large inconsistent linear systems. *Math. Program.*, 111(1-2, Ser. B):273–300, 2008.
- [38] G. W. Stewart. On the perturbation of pseudo-inverses, projections and linear least squares problems. *SIAM Rev.*, 19(4):634–662, 1977.
- [39] Z. Sun, L. Wu, and Z. Liu. A damped semismooth Newton method for the Brugnano-Casulli piecewise linear system. *BIT*, 55(2):569–589, 2015.
- [40] M. Tan, G.-L. Tian, H.-B. Fang, and K. W. Ng. A fast EM algorithm for quadratic optimization subject to convex constraints. *Statist. Sinica*, 17(3):945–964, 2007.
- [41] S. Xu. Estimation of the convergence rate of Dykstra’s cyclic projections algorithm in polyhedral case. *Acta Math. Appl. Sinica (English Ser.)*, 16(2):217–220, 2000.