

# Matrix Criteria for the Pseudo- $P$ -Convexity of a Quadratic Form

Zvi First

*Faculty of Industrial Engineering and Management  
Technion – Israel Institute of Technology  
Haifa, 32000, Israel*

Steven T. Hackman

*School of Industrial and Systems Engineering  
Georgia Institute of Technology  
Atlanta, Georgia, 30332*

and

Ury Passy

*Faculty of Industrial Engineering and Management  
Technion – Israel Institute of Technology  
Haifa, 32000, Israel*

Submitted by Moshe Goldberg

---

## ABSTRACT

Except for the family of quasiconvex quadratic functions, no characterization of *generalized convex* quadratic forms on convex sets in  $\mathbf{R}^k$  exists. We characterize pseudo- $P$ -convex quadratic functions (i.e., bi-pseudoconvex quadratics for which every stationary point is a global minimum) on solid convex sets in  $\mathbf{R}^n \times \mathbf{R}^m$ .

---

## 1. INTRODUCTION

Let  $\mathbf{R}^k$  denote the  $k$ -dimensional Euclidean space, and let  $\mathcal{C} \subset \mathbf{R}^k$  be an open, convex set. A real valued function

$$\phi: \mathcal{C} \rightarrow \mathbf{R}$$

is called *pseudoconvex* (Tuy [30]) if

$$(\tilde{z}_2 - \tilde{z}_1)^T \nabla \phi(\tilde{z}_1) \geq 0 \quad \text{implies} \quad \phi(\tilde{z}_2) \geq \phi(\tilde{z}_1) \quad (1.1)$$

for all column vectors  $\tilde{z}_1, \tilde{z}_2 \in \mathcal{C}$ . Here,  $T$  denotes the transpose, and  $\nabla$  denotes the gradient, i.e.,

$$\nabla \phi(\tilde{z}) = \left[ \frac{\partial \phi(\tilde{z})}{\partial \zeta_1}, \frac{\partial \phi(\tilde{z})}{\partial \zeta_2}, \dots, \frac{\partial \phi(\tilde{z})}{\partial \zeta_k} \right]^T, \quad \tilde{z} = [\zeta_1, \zeta_2, \dots, \zeta_k]^T.$$

Pseudoconvex functions possess the *local-global* property, namely, every local minimum of  $\phi$  in  $\mathcal{C}$  is a global minimum. Consequently, such functions are used for modeling optimization problems, since virtually all nonlinear programming algorithms are designed to converge to a local minimum, and it is therefore desired that every local minimum be a global minimum. Mangasarian [23] has shown that pseudoconvex functions belong to the more general class of *quasiconvex* functions, whose lower level sets are convex. Quasiconvex functions play an important role in modeling various economic phenomena (see, for example, [3, 12, 28]).

A variety of optimization models involve *bifunctions*, that is, functions  $f(x, y)$  of two vector variables defined on some open convex set  $\mathcal{C}_1 \times \mathcal{C}_2 \subset \mathbf{R}^n \times \mathbf{R}^m$ . Bifunctions which arise in modeling optimization problems are typically *bipseudoconvex*, i.e.,  $f(x, y_0)$  and  $f(x_0, y)$  are each pseudoconvex for all fixed  $x_0$  and  $y_0$ , but not necessarily pseudoconvex in  $(x, y)$  when considered as a single variable in  $\mathbf{R}^{n+m}$ . Bifunctions are used, for example, in bilinear programming, parametric optimization, and sensitivity problems [1, 2, 5, 22].

Bifunctions do not usually satisfy (1.1). Such functions, however, possess the abovementioned local-global property if they satisfy the following natural analogue of (1.1):

$$\left. \begin{aligned} (x_2 - x_1)^T \nabla_x f(x_1, y_1) &\geq 0 \\ (y_2 - y_1)^T \nabla_y f(x_1, y_1) &\geq 0 \end{aligned} \right\} \quad \text{imply} \quad f(x_2, y_2) \geq f(x_1, y_1) \quad (1.2)$$

for all  $(x_1, y_1), (x_2, y_2) \in \mathcal{C}_1 \times \mathcal{C}_2$ . A function  $f(x, y)$  satisfying (1.2) is called *pseudo-P-convex* (Hackman and Passy [17]). Pseudo-P-convex functions arise quite naturally as nondecreasing superpositions of pseudoconvex functions, since for every two pseudoconvex functions  $g: \mathcal{C}_1 \rightarrow \mathbf{R}$  and  $h: \mathcal{C}_2 \rightarrow \mathbf{R}$ , and

every nondecreasing function  $F : \mathbf{R}^2 \rightarrow \mathbf{R}$ , the function  $f(x, y) = F(g(x), h(y))$  is pseudo- $P$ -convex.

From a practical point of view, it is difficult to verify whether a function is pseudoconvex or pseudo- $P$ -convex, since (1.1) and (1.2) involve an infinite number of linear inequalities. This problem has motivated researchers to investigate nonconvex quadratic functions [7, 9, 21, 25, and 27].

From the modeling perspective (cf. [21, 29, 32]), it is important to determine whether a stationary point of a quadratic objective function, restricted to a given convex set, is a global minimum. This is related to the question of whether the quadratic function is convex, pseudoconvex, or pseudo- $P$ -convex on the convex set in question. Most commonly, the set is the nonnegative orthant. Except for the family of quasiconvex quadratic functions, no matrix characterization of *generalized convex* quadratic functions on *solid* convex sets (i.e. convex sets with nonempty interior) in  $\mathbf{R}^k$  exists.

The main purpose of this paper is to characterize quadratic functions (i.e. quadratic forms)  $f$  which are pseudo- $P$ -convex in the sense of (1.2), on a solid convex subset  $\mathcal{C}_1 \times \mathcal{C}_2$  of  $\mathbf{R}^n \times \mathbf{R}^m$ . We show that such quadratic forms have at most two negative eigenvalues. Quadratic forms with negative eigenvalues cannot be pseudo- $P$ -convex on the whole space  $\mathbf{R}^n \times \mathbf{R}^m$ ; i.e., (1.2) does not hold on the whole space. Instead, for a given quadratic form  $f$  we characterize a subset  $\mathcal{D}$  of  $\mathbf{R}^n \times \mathbf{R}^m$  such that  $f$  is pseudo- $P$ -convex on the open convex set  $\mathcal{C}_1 \times \mathcal{C}_2$  if and only if  $\mathcal{C}_1 \times \mathcal{C}_2 \subseteq \mathcal{D}$ . In this sense  $\mathcal{D}$  is a *maximal domain of pseudo- $P$ -convexity* for  $f$ . The set  $\mathcal{D}$  is defined by a fourth order polynomial. While  $\mathcal{D}$  is never convex, we extract three pairs of disjoint convex cones contained in  $\mathcal{D}$ . These pairs of convex cones are characterized by quadratic forms.

Section 2 summarizes the necessary mathematical preliminaries. In particular, we discuss a characterization of pseudo- $P$ -convexity; a characterization due to Chabrilac and Crouzeix [7] of when the restriction of a quadratic form on  $\mathbf{R}^k$  to the null space of an  $s \times k$  matrix is positive semidefinite; and some fundamental results on the Schur complement. Section 3 develops the criteria for pseudo- $P$ -convexity. In Section 4 the maximal subset of pseudo- $P$ -convex quadratics is defined, and illustrative examples are provided in Section 5.

## 2. MATHEMATICAL PRELIMINARIES

Pseudoconvex quadratic functions which are not convex are called *merely pseudoconvex* functions. Quadratic functions are never merely pseudoconvex

on the whole of  $\mathbf{R}^k$  [25]. Martos [25] was the first to characterize merely pseudoconvex functions on the semipositive orthant (we call a vector semipositive if it is entrywise nonnegative and at least one of its components is positive). For a given matrix  $Q$ , Cottle and Ferland [9], Crouzeix and Ferland [10], and Ferland [14] have provided matrix criteria for a quadratic form  $z^T Qz$  to be merely pseudoconvex on a solid convex set. In general, Ferland [14] and Schaible [27] have shown that  $Q$  can have at most one negative eigenvalue. Moreover, a quadratic form with exactly one negative eigenvalue is pseudoconvex on any solid convex set<sup>1</sup>  $\mathcal{C}$  if and only if  $\mathcal{C}$  is contained in the union of the disjoint convex cones

$$\mathcal{D}^- = \{z \in \mathbf{R}^k : z^T Qz \leq 0 \text{ and } v^T z > 0\} \cup \{z \in \mathbf{R}^k : z^T Qz \leq 0 \text{ and } v^T z < 0\}, \tag{2.1}$$

where  $v$  is the eigenvector associated with the negative eigenvalue of  $Q$ . In this sense Equation (2.1) defines the *maximal domain of pseudoconvexity*.

If  $Q$  is nonsingular, then (2.1) is equivalent to

$$\mathcal{D}^- = \{z \in \mathbf{R}^k : z^T Qz \leq 0, z \neq 0\}, \tag{2.2}$$

and it can be shown [14] that

$$\mathcal{D}^- = \{z \in \mathbf{R}^k : d^T Qz = 0 \text{ for some } d \in \mathbf{R}^k \text{ implies } d^T Qd \geq 0\}. \tag{2.3}$$

Diewert et al. [13] showed that a continuously differentiable function  $\phi$  defined on  $\mathbf{R}^k$  is pseudoconvex on a convex subset  $\mathcal{C} \subset \mathbf{R}^k$  if and only if for all  $z_1, z_2 \in \mathcal{C}$

$$(z_2 - z_1)^T \nabla \phi(z_1) = 0 \implies \phi(z_1) = \min_{0 \leq \gamma \leq 1} \phi(z_1 + \gamma(z_2 - z_1)). \tag{2.4}$$

For quadratic pseudoconvex forms  $z^T Qz$ , (2.4) becomes

$$(z_2 - z_1)^T Qz_1 = 0 \implies (z_2 - z_1)^T Q(z_2 - z_1) \geq 0. \tag{2.5}$$

---

<sup>1</sup>This result does not necessarily hold for convex sets without interior. Consider the example  $f(x, y) = x^T Q_1 x - y^T Q_2 y$  where  $Q_1$  is positive definite but  $Q_2$  is an arbitrary matrix. Then on the set  $\{(x, y) : x \in \mathbf{R}^k, y = 0\}$  the function is convex and hence pseudoconvex.

Since  $\mathcal{D}^-$  in (2.3) is the maximal domain of pseudoconvexity, it follows from (2.5) that a quadratic form is pseudoconvex on a solid convex set  $\mathcal{C} \subset \mathbf{R}^k$  if and only if

$$d^T Qz = 0 \Rightarrow d^T Qd \geq 0 \quad \text{for all } z \in \mathcal{C}. \tag{2.6}$$

The question of when the restriction of a quadratic form on  $\mathbf{R}^k$  to the null space of an  $s \times k$  matrix is positive semidefinite has been extensively investigated by Hancock [18], Mann [24], Samuelson [26], Debreu [11], Bellman [6], and Hestenes [20]. Crouzeix and Ferland [10] and Schaible [27] dealt with the special case  $s = 1$ . Recently, Chabrilac and Crouzeix [7] unified all these results using Schur complement theory. Based on these results, it is possible to obtain (2.6) (see also Crouzeix and Ferland [10]).

The following result is used for the development of our criteria:

**THEOREM 1** (Chabrilac and Crouzeix [7]). *Let  $K$  be a symmetric  $k \times k$  matrix,  $m$  and let  $L$  be a  $k \times s$  matrix of full column rank. Then  $z^T Kz \geq 0$  for all  $z$  such that  $z^T L = 0$  if and only if the bordered matrix*

$$\begin{bmatrix} K & \vdots & L \\ \vdots & \ddots & \vdots \\ L^T & \vdots & 0 \end{bmatrix}$$

*has exactly  $s$  negative eigenvalues.*

The following theorem characterizes pseudo- $P$ -convex functions which are continuously differentiable and bi-pseudoconvex.

**THEOREM 2.** *Let  $f: \mathbf{R}^n \times \mathbf{R}^m \rightarrow \mathbf{R}$  be a continuously differentiable function. Then  $f$  is pseudo- $P$ -convex on the convex set  $\mathcal{C}_1 \times \mathcal{C}_2$  if and only if*

$$\left. \begin{aligned} (x_2 - x_1)^T \nabla_x f(x_1, y_1) &= 0 \\ (y_2 - y_1)^T \nabla_y f(x_1, y_1) &= 0 \end{aligned} \right\} \Rightarrow f(x_1, y_1) = \min_{0 \leq \alpha, \beta \leq 1} f(x_1 + \alpha(x_2 - x_1), y_1 + \beta(y_2 - y_1)) \tag{2.7}$$

*holds for all  $(x_1, y_1), (x_2, y_2) \in \mathcal{C}_1 \times \mathcal{C}_2$ .*

*Proof.* It is immediate from the definition (1.2) that every pseudo- $P$ -convex function satisfies (2.7) (here the assumption of continuous differen-

tiability is not required.) As for the converse, pick  $(x_1, y_1), (x_2, y_2) \in \mathcal{C}_1 \times \mathcal{C}_2$  such that  $(x_2 - x_1)^T \nabla_x f(x_1, y_1) \geq 0$  and  $(y_2 - y_1)^T \nabla_y f(x_1, y_1) \geq 0$ . Note that if  $x_1 = x_2$ , then by identifying  $z$  with  $y$  and  $\phi$  with  $f(x_1, \cdot)$ , (2.7) becomes (2.4) and it follows that for a given  $x_1$ ,  $f(x_1, \cdot)$  is pseudoconvex. Similarly, if  $y_1 = y_2$ , (2.4) shows that  $f(\cdot, y_1)$  is pseudoconvex. Thus,  $f$  is a bi-pseudoconvex function.

We must show that  $f(x_2, y_2) \geq f(x_1, y_1)$ . Define

$$h(\alpha, \beta) = f(x_1 + \alpha(x_2 - x_1), y_1 + \beta(y_2 - y_1)).$$

Note that  $h$  is continuously differentiable, bi-pseudoconvex function that satisfies (2.7). The proof will follow if we can argue that  $h(1, 1) \geq h(0, 0)$ .

Consider the set

$$\mathcal{D} = \{(\alpha, \beta) \in [0, 1] \times [0, 1] : \nabla h(\alpha, \beta) \geq 0 \text{ and } h(\alpha, \beta) \geq h(0, 0)\}.$$

Clearly,  $(0, 0) \in \mathcal{D}$  and so  $\mathcal{D}$  is nonempty. Maximize the sum  $\alpha + \beta$  over  $\mathcal{D}$ . Since  $h$  is continuously differentiable and the unit square is compact, a maximal element  $(\alpha^*, \beta^*)$  exists. If  $\nabla h(\alpha^*, \beta^*) = 0$ , then (2.7) guarantees that  $h(1, 1) \geq h(0, 0)$ . Suppose, however, that both partial derivatives of  $h$  at  $(\alpha^*, \beta^*)$  are positive. Since  $(\alpha^*, \beta^*)$  is a maximal element,  $(\alpha^*, \beta^*) = (1, 1)$ . Consequently,  $h(1, 1) \geq h(0, 0)$ . Without loss of generality, suppose finally that

$$\frac{\partial}{\partial \alpha} h(\alpha^*, \beta^*) = 0 \quad \text{and} \quad \frac{\partial}{\partial \beta} h(\alpha^*, \beta^*) > 0.$$

Since  $h(\cdot, \beta^*)$  is pseudoconvex,

$$h(\alpha^*, \beta^*) = \min_{0 \leq \alpha \leq 1} h(\alpha, \beta^*). \quad (2.8)$$

Suppose  $\alpha^* < 1$ . Since  $h$  is continuously differentiable, (2.8) implies that there exists  $\varepsilon > 0$  for which both partial derivatives of  $h$  at  $(\alpha^* + \varepsilon, \beta^*)$  are nonnegative, once again contradicting the maximality of  $(\alpha^*, \beta^*)$ . Therefore  $\alpha^* = 1$ . Now, since  $h(1, \beta)$  is pseudoconvex, it follows immediately that  $h(1, 1) \geq h(1, \beta^*) \geq h(0, 0)$ , as required. ■

We conclude this section with a brief review of the Schur complement theory (see Chabrilac and Crouzeix [7] and Haynsworth [19]), which we shall use in the sequel. Given a real symmetric  $k \times k$  matrix  $K$ , the *inertia*

of  $K$ , denoted as usual by  $\text{In}(K)$  is the triple  $(\pi(K), \nu(K), \delta(K))$  consisting of a number of positive, negative, and zero eigenvalues of  $K$ , so that  $\pi(K) + \nu(K) + \delta(K) = k$ . Given the partition

$$K = \begin{bmatrix} K_1 & K_3 \\ K_3^T & K_2 \end{bmatrix}$$

of  $K$ , where  $K_1, K_2$ , and  $K_3$  are  $n \times n, m \times m$ , and  $n \times m$ , respectively, the Schur complement of  $K_1$  in  $K$  is  $K/K_1 \equiv K_2 - K_3^T K_1^{-1} K_3$ , assuming that  $K_1$  is nonsingular. Similarly, the Schur complement of  $K_2$  in  $K$  is  $K/K_2 \equiv K_1 - K_3 K_2^{-1} K_3^T$ . In either case,

$$\det K = \det K_i \det K/K_i, \quad i = 1, 2. \tag{2.9}$$

Finally, the inertia of  $K$  may be determined from the inertias of  $K_i$  and the Schur complement  $K/K_i$  by the equation

$$\text{In}(K) = \text{In}(K_i) + \text{In}(K/K_i), \quad i = 1, 2. \tag{2.10}$$

### 3. MATRIX CRITERIA FOR PSEUDO-*P*-CONVEXITY

Consider the following quadratic form:

$$f(u) = \frac{1}{2} u^T Q u = \frac{1}{2} [x^T, y^T] \begin{bmatrix} Q_1 & Q_3 \\ Q_3^T & Q_2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}, \quad u = \begin{bmatrix} x \\ y \end{bmatrix}. \tag{3.1}$$

Throughout this paper we assume, unless otherwise stated, that  $Q_1, Q_2$ , and  $Q$  are symmetric and nonsingular. Consider the matrices

$$V = [Q_1 \ \vdots \ Q_3] \quad \text{and} \quad W = [Q_3^T \ \vdots \ Q_2].$$

Note that  $Vu = \nabla_x f(u)$  and  $Wu = \nabla_y f(u)$ .

By Theorem 2,  $f(u)$  in (3.1) is pseudo-*P*-convex on some solid convex domain  $\mathcal{C}_1 \times \mathcal{C}_2 \subset \mathbf{R}^n \times \mathbf{R}^m$  if and only if

$$\left. \begin{aligned} (x_2 - x_1)^T V u_1 &= 0 \\ (y_2 - y_1)^T W u_1 &= 0 \end{aligned} \right\} \Rightarrow ((x_2 - x_1)^T, (y_2 - y_1)^T) Q ((x_2 - x_1), (y_2 - y_1)) \geq 0 \tag{3.2}$$

for all  $u_1 = (x_1, y_1), u_2 = (x_2, y_2) \in \mathcal{C}_1 \times \mathcal{C}_2$ . For a point  $u$  in the interior of  $\mathcal{C}_1 \times \mathcal{C}_2$  instead of (3.2) we can write

$$\left. \begin{aligned} d_1^T \nabla_x f(u) = d_1^T Vu = 0 \\ d_2^T \nabla_y f(u) = d_2^T Wu = 0 \end{aligned} \right\} \Rightarrow \begin{bmatrix} d_1^T & d_2^T \end{bmatrix} Q \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} \geq 0 \quad (3.3)$$

for all  $(d_1, d_2) \in \mathbf{R}^n \times \mathbf{R}^m$ .

It will be shown in Theorem 3 that (3.3) holds even for boundary points of  $\mathcal{C}_1 \times \mathcal{C}_2$ , except possibly for points where the partial gradients  $\nabla_x f(u), \nabla_y f(u)$  vanish.

If we identify

$$z = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}, \quad L = \begin{bmatrix} Vu & \vdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \vdots & Wu \end{bmatrix}, \quad K = Q, \quad s = 2, \quad \text{and} \quad k = n + m,$$

then Theorem 1 implies that the matrix

$$\begin{bmatrix} K & \vdots & L \\ \vdots & \ddots & \vdots \\ L^T & \vdots & 0 \end{bmatrix}$$

has exactly two negative eigenvalues; hence  $Q$  has at most two negative eigenvalues, and this is a necessary condition for the pseudo- $P$ -convexity of  $f$ . If  $Q$  has no negative eigenvalues, then clearly  $f$  is convex on the whole of  $\mathbf{R}^n \times \mathbf{R}^m$  and no further discussion is required.

We now turn to the case when  $Q$  has one negative eigenvalue. The case when  $Q$  has two negative eigenvalues will be examined later.

Hereafter, the expression  $f$  is pseudo- $P$ -convex at a point  $u = (x, y) \in \mathcal{C}_1 \times \mathcal{C}_2$  means that (3.3) holds. Pseudoconvexity implies pseudo- $P$ -convexity; thus  $f$  is pseudo- $P$ -convex at each  $u \in \mathcal{D}^-$  (2.6). Since  $Q$  has a negative eigenvalue,  $f$  is not pseudo- $P$ -convex at the origin. Therefore, we have to consider only the set

$$\mathcal{D}^+ = \{u = (x, y) : u^T Qu > 0\}. \quad (3.4)$$

The following well-known *interlacing* lemma is critical to the proof of the next theorem.



LEMMA 1 [15, p. 269]. *Let  $A$  be an  $n \times n$  symmetric matrix, let  $A_r$  denote its leading  $r \times r$  principle submatrix, and let  $\lambda_i(A_r)$ ,  $1 \leq i \leq r$ , denote the value of the  $i$ th largest eigenvalue of the matrix  $A_r$ . Then*

$$\begin{aligned} \lambda_{r+1}(A_{r+1}) &\leq \lambda_r(A_r) \leq \lambda_r(A_{r+1}) \leq \dots \\ &\leq \lambda_2(A_r) \leq \lambda_2(A_{r+1}) \leq \lambda_1(A_r) \leq \lambda_1(A_{r+1}). \end{aligned}$$

THEOREM 3. *The quadratic function  $f$  is pseudo-P-convex at  $u \in \mathcal{D}^+$  if and only if  $\nabla_x f(u) \neq 0$ ,  $\nabla_y f(u) \neq 0$ , and*

$$\begin{aligned} u^T Q u \{ u^T W^T (Q/Q_1)^{-1} W u \} - (u^T W^T y)^2 \\ = u^T Q u \{ u^T V^T (Q/Q_2)^{-1} V u \} - (u^T V^T x)^2 \leq 0. \end{aligned} \tag{3.5}$$

REMARK 1. *Neither of the partial gradients  $\nabla_x f(u)$  and  $\nabla_y f(u)$  vanishes at points where the inequalities (3.5) are strict.*

*Proof.* We first argue that a necessary condition for the pseudo-P-convexity of  $f$  at a point  $u \in \mathcal{D}^+$  is that  $\nabla_x f(u) \neq 0$  and  $\nabla_y f(u) \neq 0$ . Indeed, when  $\nabla_x f(u)$  or  $\nabla_y f(u)$  vanishes, the condition (3.3) is equivalent to (2.6); hence  $u \in \mathcal{D}^-$ , contradicting the assumption that  $u \in \mathcal{D}^+$ . Consequently, the statement of the theorem is trivially true in this case. We now assume that either  $\nabla_x f(u) \neq 0$  and  $\nabla_y f(u) \neq 0$ . By Theorem 1, the function  $f$  is pseudo-P-convex at  $u \in \mathcal{D}^+$  if and only if the bordered matrix

$$B(u) = \begin{bmatrix} Q_1 & Q_3 & \vdots & \nabla_x f(u) & 0 \\ Q_3^T & Q_2 & \vdots & 0 & \nabla_y f(u) \\ \dots & \dots & \dots & \dots & \dots \\ \nabla_x^T f(u) & 0 & \vdots & 0 & 0 \\ 0 & \nabla_y^T f(u) & \vdots & 0 & 0 \end{bmatrix}$$

has exactly two negative eigenvalues. Add the last row and column of  $B(u)$  to its  $(n + m + 1)$ st row and column to obtain the matrix

$$D(u) = \begin{bmatrix} Q_1 & Q_3 & \vdots & \nabla f(u) & 0 \\ Q_3^T & Q_2 & \vdots & \vdots & \nabla_y f(u) \\ \dots & \dots & \dots & \dots & \dots \\ \nabla^T f(u) & 0 & \vdots & 0 & 0 \\ 0 & \nabla_y^T f(u) & \vdots & 0 & 0 \end{bmatrix}$$

Of course,  $\nu(D(u)) = \nu(B(u))$ . We shall think of  $D(u)$  as a matrix obtained from

$$Q = \begin{bmatrix} Q_1 & Q_3 \\ Q_3^T & Q_2 \end{bmatrix}$$

in two steps, as follows:

$$Q \rightarrow C(u) = \begin{bmatrix} Q_1 & Q_3 & \vdots \\ Q_3^T & Q_2 & \nabla f(u) \\ \vdots & \vdots & \ddots \\ \nabla^T f(u) & \vdots & 0 \end{bmatrix} \rightarrow D(u). \tag{3.6}$$

Using (2.9),

$$\det C(u) = (\det Q) [0 - \nabla^T f(u) Q^{-1} \nabla f(u)] = -(\det Q) u^T Q u,$$

which is positive, since by assumption  $\det Q < 0$  and  $u^T Q u > 0$ . From Lemma 1 it follows that the first step,  $Q \rightarrow C(u)$ , adds one negative eigenvalue, i.e.,

$$\nu(C(u)) = 2 \quad \text{and} \quad \delta(C(u)) = 0. \tag{3.7}$$

Lemma 1 together with (3.7) establishes that

$$2 \leq \nu(D(u)) + \delta(D(u)) \leq 3.$$

Consequently,  $\nu(D(u)) = 2$  if and only if

$$\det D(u) = (\det Q) \left[ u^T Q u \left( u^T W^T (Q/Q_1)^{-1} W u - \frac{1}{u^T Q u} (u^T W^T y)^2 \right) \right] \geq 0. \tag{3.8}$$

Here we have used (2.9) to calculate  $\det D(u)$  from  $\det C(u)$ .

Interchanging the roles of  $x$  and  $y$  in Theorem 2,  $f$  is pseudo- $P$ -convex at  $u \in \mathcal{Q}^+$  if and only if the bordered matrix

$$E(u) = \begin{bmatrix} Q_2 & Q_3^T & \vdots & 0 & \nabla_x f(u) \\ Q_3 & Q_1 & \vdots & \nabla_y f(u) & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \nabla_y^T f(u) & \vdots & 0 & 0 \\ \nabla_x^T f(u) & 0 & \vdots & 0 & 0 \end{bmatrix}$$

has exactly two negative eigenvalues. And, by similar reasoning to the above, this is equivalent to

$$\det E(u) = (\det Q) \left[ u^T Q u \left( u^T V^T (Q/Q_2)^{-1} V u - \frac{1}{u^T Q u} (u^T V^T x)^2 \right) \right] \geq 0. \tag{3.9}$$

The result now follows from (3.8) and (3.9), since  $\det E(u) = \det D(u)$  and  $\det Q < 0$ . ■

Note that (3.8) holds when  $u^T Q u > 0$  and  $u^T W^T (Q/Q_1)^{-1} W u \leq 0$ . Similarly, (3.9) holds when  $u^T Q u > 0$  and  $u^T V^T (Q/Q_2)^{-1} V u \leq 0$ . Note further that if  $\nabla_x f(u) = 0$  then  $u^T Q u = u^T W^T (Q/Q_1)^{-1} W u$ , and similarly, if  $\nabla_y f(u) = 0$  then  $u^T Q u = u^T V^T (Q/Q_2)^{-1} V u$ .

Motivated by these observations, we have the following corollary:

**COROLLARY 1.** *The quadratic function  $f$  is pseudo-P-convex at  $u$  if at least one of the following inequalities holds:*

- (i)  $u^T Q u \leq 0, u \neq 0$ ;
- (ii)  $u^T V^T (Q/Q_2)^{-1} V u \leq 0, \nabla_x f(u) \neq 0$ ;
- (iii)  $u^T W^T (Q/Q_1)^{-1} W u \leq 0, \nabla_y f(u) \neq 0$ .

When  $Q$  is nonsingular and has exactly two negative eigenvalues, then we have the following:

**REMARK 2.** *If  $Q$  has two negative eigenvalues and either one of the partial gradients  $\nabla_x f(u), \nabla_y f(u)$  vanishes, then the condition (3.3) cannot hold.*

This is a direct consequence of Theorem 1. It follows therefore, that in this case pseudo-P-convexity does not hold at points where a partial gradient vanishes.

**THEOREM 4.** *Suppose  $Q$  is nonsingular and has exactly two negative eigenvalues. The quadratic form  $f$  is pseudo-P-convex at  $u$  if and only if the following hold:*

- (i)  $\nabla_x f(u) \neq 0, \nabla_y f(u) \neq 0$ ,
- (ii)  $u^T Q u [u^T W^T (Q/Q_1)^{-1} W u] - (u^T W^T y)^2$   
 $= u^T Q u [u^T V^T (Q/Q_2)^{-1} V u] - (u^T V^T x)^2 \geq 0$ ,
- (iii)  $u^T Q u \leq 0$ .

*Proof.* By Remark 2,  $f$  is pseudo- $P$ -convex at  $u$  only if  $\nabla_x f(u) \neq 0$  and  $\nabla_y f(u) \neq 0$ . In this case  $\det Q > 0$  and  $C(u)$  (3.6) has two negative eigenvalues. Thus,

$$\det C(u) = (\det Q)[0 - \nabla^T f(u)Q^{-1}\nabla f(u)] = -\det(Q)u^T Qu \geq 0;$$

hence  $u^T Qu \leq 0$ . Since  $\nabla_x f(u) \neq 0$  and  $\nabla_y f(u) \neq 0$ , the matrix  $D(u)$  has also two negative eigenvalues. The rest of the proof is identical to the steps taken in Theorem 3. ■

As an immediate result we have the following corollary:

**COROLLARY 2.** *Suppose  $Q$  is nonsingular and has exactly two negative eigenvalues. If  $f$  is pseudo- $P$ -convex at  $u$ , then each of the three inequalities*

- (i)  $u^T Qu \leq 0$ ,
- (ii)  $u^T W^T(Q/Q_1)^{-1}Wu > 0$ ,
- (iii)  $u^T V^T(Q/Q_2)^{-1}Vu \leq 0$

*holds.*

*Proof.* From Theorem 4 it follows that  $u^T Qu \leq 0$ . Conditions (ii) and (iii) can be obtained if in (3.6)  $\nabla f(u)$  is replaced with  $\nabla_x f(u)$  or with  $\nabla_y f(u)$ . ■

Compare this result with Corollary 1.

#### 4. DOMAINS OF PSEUDO- $P$ -CONVEXITY OF QUADRATIC FUNCTIONS

We now suppose that a quadratic form  $f$  is given, and we wish to find whether  $f$  is pseudo- $P$ -convex on a given solid convex domain  $\mathcal{E}_1 \times \mathcal{E}_2$ . A similar question for pseudoconvex functions is addressed by Cottle and Ferland in [9].

Let  $\mathcal{D}$  be the set of all points at which  $f$  is pseudo- $P$ -convex. In view of the following corollary we call  $\mathcal{D}$  *the maximal domain of pseudo- $P$ -convexity of  $f$* . If  $\nu(Q) = 1$ , then  $\mathcal{D}$  is defined via Equation (2.3) and Theorem 3. If  $\nu(Q) = 2$ , then  $\mathcal{D}$  is defined via Theorem 4. Denote by  $\bar{\mathcal{D}}$  the closure of  $\mathcal{D}$ ; it follows from Theorems 3 and 4 that

$$\bar{\mathcal{D}} = \mathcal{D} \cup \{u : \nabla_x f(u) = 0 \text{ or } \nabla_y f(u) = 0\}. \tag{4.1}$$

COROLLARY 3. Let  $\mathcal{D}$  be the maximal domain of pseudo- $P$ -convexity.

- (i) If  $\mathcal{C}_1 \times \mathcal{C}_2 \subseteq \mathcal{D}$ , then  $f$  is pseudo- $P$ -convex on  $\mathcal{C}_1 \times \mathcal{C}_2$ .
- (ii) If  $f$  is pseudo- $P$ -convex on  $\mathcal{C}_1 \times \mathcal{C}_2$  then  $\text{int}(\mathcal{C}_1 \times \mathcal{C}_2) \subseteq \mathcal{D}$ , where  $\text{int}$  denotes the interior of a set.

*Proof.* These results follow from Equation (2.2) and Theorems 2, 3, and 4. ■

Note that when  $\mathcal{C}_1 \times \mathcal{C}_2$  is open,  $f$  is pseudo- $P$ -convex if and only if  $\mathcal{C}_1 \times \mathcal{C}_2 \subseteq \mathcal{D}$ . In general, if  $\text{int}[\mathcal{C}_1 \times \mathcal{C}_2] \subseteq \mathcal{D}$ , to determine whether  $f$  is pseudo- $P$ -convex on  $\mathcal{C}_1 \times \mathcal{C}_2$  one must check separately the boundary points, i.e., the points in  $\mathcal{C}_1 \times \mathcal{C}_2 \cap \overline{\mathcal{D}}$  which do not belong to  $\mathcal{D}$ , using the relation (3.2).

Recall that  $\mathcal{D}$  is characterized by a fourth order polynomial. However, if  $\nu(Q) = 1$  and  $Q_1$  and  $Q_2$  are positive definite, we can extract three pairs of disjoint convex cones contained in  $\mathcal{D}$  which are characterized by a quadratic form.

Let  $v$  denote a normalized eigenvector associated with the single negative eigenvalue of  $Q$ . Since  $Q_1$  and  $Q_2$  have only positive eigenvalues, it follows from (2.10) that the Schur complements  $Q/Q_1$  and  $Q/Q_2$  each have exactly one negative eigenvalue. Let  $v_1$  and  $v_2$  denote the eigenvectors associated with the single negative eigenvalues of  $Q/Q_1$  and  $Q/Q_2$ , respectively. Define

$$\mathcal{F}_1^< = \{y \in \mathbf{R}^m : y^T(Q/Q_1)^{-1}y \leq 0 \text{ and } y^T v_1 < 0\},$$

$$\mathcal{F}_1^> = \{y \in \mathbf{R}^m : y^T(Q/Q_1)^{-1}y \leq 0 \text{ and } y^T v_1 > 0\},$$

$$\mathcal{F}_2^< = \{x \in \mathbf{R}^n : x^T(Q/Q_2)^{-1}x \leq 0 \text{ and } x^T v_2 < 0\},$$

$$\mathcal{F}_2^> = \{x \in \mathbf{R}^n : x^T(Q/Q_2)^{-1}x \leq 0 \text{ and } x^T v_2 > 0\}.$$

The sets  $\mathcal{F}_1^<$ ,  $\mathcal{F}_1^>$ ,  $\mathcal{F}_2^<$ , and  $\mathcal{F}_2^>$  are convex cones with nonempty interior [16, p. 270]. By Corollary 1,  $f$  is pseudo- $P$ -convex on any solid convex set  $\mathcal{C}_1 \times \mathcal{C}_2$  if this set lies in the union of the following three cones, each a union of two disjoint convex sets:

$$\mathcal{F}_1 \equiv \{u : Wu \in \mathcal{F}_1^>\} \cup \{u : Wu \in \mathcal{F}_1^<\},$$

$$\mathcal{F}_2 \equiv \{u : Vu \in \mathcal{F}_2^>\} \cup \{u : Vu \in \mathcal{F}_2^<\},$$

$$\mathcal{F}_3 \equiv \{u \in \mathcal{D}^- : u^T v < 0\} \cup \{u \in \mathcal{D}^- : u^T v > 0\}.$$

From the modeling perspective (cf. [21, 29, 32]), it is important to determine whether a Kuhn-Tucker stationary point of a quadratic objective function defined on the nonnegative orthant is a global minimum. This question is related to the question of whether the quadratic function is convex, pseudoconvex, or pseudo- $P$ -convex on the nonnegative orthant. The next paragraph deals with this question. The following definition is required.

**DEFINITION 1** [4]. An  $n \times n$  symmetric matrix  $A$  is *conegative* (copositive) if  $p^T A p \leq 0$  ( $p^T A p \geq 0$ ) for all  $p \geq 0$ .

A test for conegativity is provided in [8]. Clearly, a matrix  $A$  is conegative if all its entries are nonpositive. A test for conegativity on the intersection of the nonnegative orthant with any polyhedral cone is given in [31].

**COROLLARY 4.** Let  $Q$  be a nonsingular symmetric matrix with a single negative eigenvalue. Then the quadratic form  $u^T Q u$  is pseudo- $P$ -convex on the semipositive orthant if any of the following three conditions holds:

- (a)  $Q$  is conegative.
- (b) The matrix  $W^T(Q/Q_1)^{-1}W$  is conegative, and  $Q$  is also conegative but only on the cone  $\{u = (x, y) : \nabla_y^T f(u) = [x^T, y^T]W^T = 0\} \cap \{u = (x, y) \geq 0\}$ .
- (c) The matrix  $V^T(Q/Q_2)^{-1}V$  is conegative, and  $Q$  is also conegative but only on the cone  $\{u = (x, y) : \nabla_x^T f(u) = [x^T, y^T]V^T = 0\} \cap \{u = (x, y) \geq 0\}$ .

*Proof.* The proof follows immediately from Corollary 1 by observing that whenever the partial gradients vanish, conditions (b) and (c) in Corollary 4 imply  $u^T Q u \leq 0$ , i.e., condition (i) in Corollary 1 holds. ■

For a vector  $z$  the expression  $z \not\leq 0$  denotes that some components of  $z$  are positive. The partial gradients of the quadratic form do not vanish on the semipositive orthant when the following holds.

**COROLLARY 5.** If  $Q_2^{-1}Q_3^T x \not\leq 0$  ( $Q_1^{-1}Q_3 y \not\leq 0$ ) on the semipositive orthant and if  $W^T(Q/Q_1)^{-1}W$  ( $V^T(Q/Q_2)^{-1}V$ ) is conegative, then  $Q$  is pseudo- $P$ -convex on the semipositive orthant.

*Proof.* The proof is a direct consequence of Corollary 4. The partial gradients of  $f(u)$ ,  $\nabla_y^T f(u) = [x^T, y^T]W^T = x^T Q_3 + y^T Q_2$  and  $\nabla_x^T f(u) = [x^T, y^T]V^T = x^T Q_1 + y^T Q_3^T$ , do not vanish on the semipositive orthant if  $Q_2^{-1}Q_3^T x \not\leq 0$  or  $Q_1^{-1}Q_3 y \not\leq 0$ , respectively. ■

5. PSEUDO- $P$ -CONVEX QUADRATIC FUNCTIONS ON THE SEMIPOSITIVE ORTHANT

The examples in this section illustrate the above results. More specifically, we characterize  $(n + 1) \times (n + 1)$  matrices of the form

$$Q = \begin{bmatrix} Q_1 & q \\ q^T & \alpha \end{bmatrix},$$

with one or two negative eigenvalues, whose associated quadratic form

$$f(u) = \frac{1}{2} [x^T Q_1 x + 2x^T q y + \alpha y^2] \tag{5.1}$$

is pseudo- $P$ -convex on the semipositive orthant of  $\mathbf{R}^n \times \mathbf{R}$ . Here,  $Q_1$  is an  $n \times n$  matrix and  $q$  is an  $n$ -vector.

We begin by examining the case when  $Q$  has exactly one negative eigenvalue. Let  $\mathcal{D}^-$  be defined as in (2.2), and let  $u \in \mathcal{D}^-$ . Then  $f$  is pseudoconvex and therefore pseudo- $P$ -convex. When  $u \in \mathcal{D}^+ = \{u : u^T Q u > 0\}$  we know from Theorem 3 that  $f$  is pseudo- $P$ -convex at  $u$  if and only if

$$\nabla_y^T f(u) = [x^T, y] \begin{bmatrix} q \\ \alpha \end{bmatrix} \neq 0, \tag{5.2}$$

$$\nabla_x^T f(u) = [x^T, y] \begin{bmatrix} Q_1 \\ q^T \end{bmatrix} \neq 0, \tag{5.3}$$

$$u^T Q u \left( [x^T, y] \begin{bmatrix} q \\ \alpha \end{bmatrix} (\alpha - q^T Q_1^{-1} q)^{-1} [q^T, \alpha] \begin{bmatrix} x \\ y \end{bmatrix} \right) - \left( [x^T, y] \begin{bmatrix} q \\ \alpha \end{bmatrix} y \right)^2 \leq 0. \tag{5.4}$$

When (5.2) holds, (5.4) simplifies to

$$\frac{1}{\alpha - q^T Q_1^{-1} q} - \frac{y^2}{u^T Q u} \leq 0. \tag{5.5}$$

We should consider four cases:

- (a) the biconvex case, i.e.,  $Q_1$  is positive definite and  $\alpha > 0$ ;
- (b) the convex-pseudoconvex case, i.e.,  $Q_1$  is positive definite and  $\alpha < 0$ ;
- (c) the pseudoconvex-convex case, i.e., the matrix  $Q_1$  defines a merely pseudoconvex quadratic and  $\alpha > 0$ ; and
- (d) the bi-pseudoconvex case, i.e., the matrix  $Q_1$  defines a merely pseudoconvex quadratic and  $\alpha < 0$ .

We examine each case separately.

(a) *The Biconvex Case*

Since  $Q$  has exactly one negative eigenvalue, we know from Schur complement theory that

$$\alpha - q^T Q_1^{-1} q < 0. \quad (5.6)$$

It is immediate from (5.5) and (5.6) that  $f$  is pseudo- $P$ -convex on the semipositive orthant except at points where  $\nabla_y f(u)$  or  $\nabla_x f(u)$  vanishes.

When  $\nabla_y f(u) = 0$ , then

$$x = -Q_1^{-1} q y; \quad (5.7)$$

consequently,

$$u^T Q u = \frac{1}{2} y^2 (\alpha - q^T Q_1^{-1} q), \quad (5.8)$$

which is negative by (5.6). Thus when  $\nabla_x f(u) = 0$ , we have  $u \in \mathcal{D}^-$ , and  $f$  is pseudoconvex and hence pseudo- $P$ -convex.

When  $\nabla_y f(u) = 0$ , then

$$y = -x^T q / \alpha. \quad (5.9)$$

Here we have to consider two possibilities:

(i) If  $q \geq 0$ , then  $f$  is pseudo- $P$ -convex on the semipositive orthant. An example of a biconvex quadratic with  $q \geq 0$  is given by the matrix<sup>2</sup>

$$Q = \begin{bmatrix} 1 & 0 & \vdots & 3 \\ 0 & 1 & \vdots & 3 \\ \vdots & \vdots & \ddots & \vdots \\ 3 & 3 & \vdots & 1 \end{bmatrix}.$$

<sup>2</sup>If  $f$  is pseudo- $P$ -convex on the semipositive orthant, then it is pseudo- $P$ -convex on the nonnegative orthant if and only if the relation (1.2) holds at the origin. Here this condition is



(ii) If  $q \neq 0$ , then it follows by substituting (5.9) in (5.1) that  $f$  is pseudo- $P$ -convex on the semipositive orthant if

$$u^T Q u = \frac{1}{2} x^T \left( Q_1 - \frac{q q^T}{\alpha} \right) x \leq 0 \quad \text{on the conc } \{x : x \geq 0, x^T q \leq 0\}. \quad (5.10)$$

A test for (5.10) is given in [31]. Note that when  $q \leq 0$ , (5.10) simplifies to the conegativity of  $Q_1 - q q^T / \alpha$ . Since  $Q_1 - q q^T / \alpha$  is the Schur complement of  $Q$ , it is a nonsingular matrix with a single negative eigenvalue. By a simple inductive argument using Lemma 1, it can be shown that a nonsingular matrix with a single negative eigenvalue is conegative if and only if all its elements are nonpositive. An example of a biconvex quadratic with  $q \leq 0$  is given by the matrix

$$Q = \begin{bmatrix} 1 & 0 & \cdots & -3 \\ 0 & 1 & \cdots & -3 \\ \cdots & \cdots & \cdots & \cdots \\ -3 & -3 & \cdots & 1 \end{bmatrix}.$$

*(b) The Convex-Pseudoconvex Case*

The mere pseudoconvexity of  $f(x^*, y)$  for a fixed  $x^*$  assures that the partial gradient with respect to  $y$ ,  $\nabla_y f(u)$ , does not vanish [25]. As shown in case (a), it is still true that when  $\nabla_x f(u)$  vanishes,  $u \in \mathcal{D}^-$ . Thus, in the present case,  $f$  is pseudo- $P$ -convex on the semipositive orthant.

An example of a convex-pseudoconvex quadratic is given by the matrix

$$Q = \begin{bmatrix} 1 & 0 & \cdots & -3 \\ 0 & 1 & \cdots & -3 \\ \cdots & \cdots & \cdots & \cdots \\ -3 & -3 & \cdots & -1 \end{bmatrix}.$$

*(c) The Pseudoconvex-Convex Case*

For each fixed nonnegative  $y^*$ ,  $f(x, y^*)$  is merely pseudoconvex; therefore  $Q_1 \leq 0$ ,  $q \leq 0$ , and  $q^T Q_1^{-1} q \leq 0$  [25]. Assume that the partial gradients  $\nabla_x f(u)$ ,  $\nabla_y f(u)$  do not vanish, and  $u \notin \mathcal{D}^-$ . With these assumptions (5.5)

equivalent to the copositivity of  $Q$ . The following example satisfies this condition and is therefore pseudo- $P$ -convex on the nonnegative orthant, including the origin.

becomes

$$u^T Q u - \alpha y^2 + q^T Q_1^{-1} q y^2 \leq 0.$$

It follows that

$$x^T Q_1 x + 2x^T q y + \alpha y^2 - \alpha y^2 + q^T Q_1^{-1} q y^2 \leq 0,$$

or equivalently

$$\begin{bmatrix} x^T, y^T \end{bmatrix} \begin{bmatrix} Q_1 & q \\ q^T & q^T Q_1^{-1} q \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \leq 0. \tag{5.11}$$

[The elements of the matrix in (5.11) are nonpositive; thus it is conegative and the inequality holds.] Therefore, the function  $f(u)$  is pseudo- $P$ -convex on the semipositive orthant, except possibly at points where  $\nabla_y f(u)$  or  $\nabla_x f(u)$  vanish. Mere pseudoconvexity of  $f(x, y^*)$  for any fixed  $y^*$  assures that  $\nabla_x f(u)$  does not vanish on this orthant [25]. It can also be shown that if  $\nabla_y f(u)$  vanishes, then  $u \in \mathcal{D}^-$ . Thus, in the present case,  $f$  is pseudo- $P$ -convex on the semipositive orthant.

An example of a pseudoconvex-convex quadratic is given by the matrix

$$Q = \begin{bmatrix} 0 & -1 & \cdots & -1 \\ -1 & \cdots & 0 & \cdots & -1 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ -1 & -1 & \cdots & \cdots & 2 \end{bmatrix}.$$

(d) *The Bi-Pseudoconvex Case*

Mere bi-pseudoconvexity of  $f(x, y^*)$  and  $f(x^*, y)$  on the corresponding semipositive orthants assures that all the entries of  $Q_1$  and  $q$  are nonpositive, and  $\alpha \leq 0$ . Hence,  $f$  satisfies Martos's criteria in [25], so  $f$  is merely pseudoconvex and therefore pseudo- $P$ -convex on the semipositive orthant.

We now turn to consider the case when  $Q$  has two negative eigenvalues. First, assume that  $f$  is pseudoconvex-convex. Then by Martos's criteria in [25] it follows that  $q \leq 0$ , and since  $\alpha > 0$ ,  $\nabla_y f(x^*, y) = q^T x^* + \alpha y$  vanishes on the positive orthant. By Remark 2, such a quadratic function is never pseudo- $P$ -convex, so the possibility that  $f$  is pseudoconvex-convex is excluded.

It remains to consider the case when  $f$  is bi-pseudoconvex. Again, by Remark 2 bi-pseudoconvexity assures that the partial gradients do not vanish on the semipositive orthant. Here, all the elements of  $Q_1$  and  $q$  are

nonpositive and  $q^T Q_1^{-1} q \leq 0$  [25]. In this case, by Corollary 2,  $u^T Q u \leq 0$  and (5.5) must hold. Equation (5.5) can be written as

$$x^T Q_1 x + 2q^T x y + q^T Q_1^{-1} q y^2 \leq 0,$$

or equivalently

$$\begin{bmatrix} x^T & y^T \end{bmatrix} \begin{bmatrix} Q_1 & q \\ q^T & q^T Q_1^{-1} q \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \leq 0.$$

The above matrix is conegative and the inequality holds on the semipositive orthant. Hence the bi-pseudoconvex function  $f$  is pseudo- $P$ -convex on the semipositive orthant.

An example of a bi-pseudoconvex quadratic is given by the matrix

$$Q = \begin{bmatrix} 0 & -1 & \vdots & -1 \\ -1 & \dots & 0 & -1 \\ \vdots & \dots & \dots & \vdots \\ -1 & -1 & \vdots & -3 \end{bmatrix}.$$

We conclude the paper by considering a  $4 \times 4$  quadratic

$$f(u) = \frac{1}{2} \begin{bmatrix} x^T & y^T \end{bmatrix} Q \begin{bmatrix} x \\ y \end{bmatrix}$$

defined on the positive orthant of  $\mathbf{R}^2 \times \mathbf{R}^2$ , where

$$Q_1 = Q_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad Q_3 = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}.$$

The Schur complement

$$(Q/Q_2) = (Q/Q_2)^{-1} = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$$

is conegative. Since the entires of  $V = [Q_1 \vdots Q_3]$  are nonnegative, the matrix  $V^T (Q/Q_2)^{-1} V$  is also conegative. Moreover, only  $\nabla_x f(u_1)$  vanishes on the boundary of the semipositive orthant, i.e., at the points of the form  $u_1 = (x_1, y_1) = (0, 0, \eta_1, 0)$ . It can easily be checked that such points satisfy (3.2) for all  $u_2$  in the nonnegative orthant. Thus, by Corollary 5 and footnote 2,  $f$  is pseudo- $P$ -convex on the nonnegative orthant.

## REFERENCES

- 1 F. A. Al-Khayyal, Biconvex Programming and Biconcave Minimization, D.Sc. Dissertation, Dept. of Operations Research, George Washington Univ., Washington, 1977.
- 2 M. Altman, Bilinear programming, *Bull. Acad. Polon. Sci. Ser. Sci. Math. Astron. et Phys.* 16:741–746 (1968).
- 3 K. J. Arrow and A. C. Enthoven, Quasi-concave programming, *Econometrica* 21:779–800 (1961).
- 4 A. Berman and R. J. Plemmons, *Nonnegative Matrices in the Mathematical Sciences*, Academic, New York, 1979.
- 5 B. Bank, J. Guddat, D. Klatte, B. Kummer, and K. Tammer, *Nonlinear Parametric Optimization*, Akademie-Verlag, Berlin, 1982.
- 6 R. E. Bellman, *Introduction to Matrix Analysis*, McGraw-Hill, New York, 1970.
- 7 Y. Chabrilac and J. P. Crouzeix, Definiteness and semidefiniteness of quadratic forms revisited, *Linear Algebra Appl.* 63:283–292 (1984).
- 8 R. W. Cottle, G. J. Habetler, and C. E. Lemke, On classes of copositive matrices, *Linear Algebra Appl.* 3:295–310 (1970).
- 9 R. W. Cottle and J. A. Ferland, Matrix-theoretic criteria for the quasiconvexity and pseudoconvexity of quadratic functions, *Linear Algebra Appl.* 5:123–136 (1972).
- 10 J. P. Crouzeix and J. A. Ferland, Criteria for quasiconvexity and pseudoconvexity relationships and comparisons, *Math. Programming* 23:193–205 (1982).
- 11 Y. Debreu, Definite and semidefinite quadratic forms, *Econometrica* 20:295–300 (1952).
- 12 W. E. Diewert, Duality approaches in microeconomics theory, in *Handbook of Mathematical Economics* (K. J. Arrow and M. D. Intriligator, Eds.), Vol. II, North-Holland, New York, 1982.
- 13 W. E. Diewert, M. Avriel, and I. Zang, Nine kinds of quasiconvexity and concavity, *J. Econom. Theory* 25:397–420 (1981).
- 14 J. A. Ferland, Maximal domains of quasi-convexity and pseudo-convexity for quadratic functions, *Math. Programming* 3:178–192 (1972).
- 15 G. H. Golub and C. Van Loan, *Matrix Computations*, North Oxford Academic Press, Oxford, 1983.
- 16 W. H. Greub, *Linear Algebra*, Springer Verlag, New York, 1967.
- 17 S. T. Hackman and U. Passy, Projectively-convex sets and functions, *J. Math. Econom.* 17:55–68 (1988).
- 18 M. Hancok, *Theory of Maxima and Minima*, Ginn, Boston, 1917; Dover, New York, 1950.
- 19 E. V. Haynsworth, Determination of the inertia of a partitioned Hermitian matrix, *Linear Algebra Appl.* 1:73–81 (1980).
- 20 M. R. Hestenes, Augmentability in optimization theory, *J. Optim. Theory Appl.* 32:427–440 (1980).
- 21 D. H. Jacobson, *Extensions of Linear-Quadratic Control, Optimization and Matrix Theory*, Academic, New York, 1977.

- 22 J. Kyparisis and A. V. Fiacco, Generalized convexity and concavity of the optimal value function in nonlinear programming, *Math. Programming* 39:285–304 (1987).
- 23 O. L. Mangasarian, *Nonlinear Programming*, McGraw-Hill, New York, 1969.
- 24 H. B. Mann, Quadratic forms with linear constraints, *Amer. Math. Monthly* 50:430–433 (1943).
- 25 B. Martos, Subdefinite matrices and quadratic forms, *SIAM J. Appl. Math.* 17:1215–1223 (1969).
- 26 P. Samuelson, *Foundations of Economic Analysis*, Harvard U.P., Cambridge, Mass., 1947, p. 448.
- 27 S. Schaible, Quasiconvex, pseudoconvex and strictly pseudoconvex quadratic functions, *J. Optim. Theory Appl.* 35:303–338 (1981).
- 28 S. Schaible and W. T. Ziemba (Eds.), *Generalized Convexity in Optimization and Economics*, Academic, New York, 1981.
- 29 W. F. Sharpe, *Portfolio Theory and Capital Markets*, McGraw-Hill, New York, 1970.
- 30 H. Tuy, Sur les inégalités linéaires, *Colloq. Math.* 13:107–123 (1964).
- 31 H. Valiaho, Testing the definiteness of matrices on polyhedral cones, *Linear Algebra Appl.* 101:135–165 (1988).
- 32 A. Zellner, Decision rules for economic forecasting, *Econometrica* 31:111–131 (1963).

*Received 16 April 1989; final manuscript accepted 3 July 1989*