



## WOLFE-TYPE DUALITY INVOLVING UNIVEX FUNCTIONS FOR A MINIMAX PROGRAMMING PROBLEM

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**ABSTRACT.** A sufficient optimality theorem is proved for a certain minimax programming problem under the assumptions of proper  $(b, \eta, \phi)$ -univex conditions on the functions involved for such a problem. A dual is defined for this problem and duality theorems relating the primal and the dual are proved. The results presented in this paper extend earlier works in the literature to a wider class of functions.

### 1. INTRODUCTION

The concept of invexity was introduced by Hanson [4] as a generalization of convexity. Later Bector and Singh [2] defined B-vexity and discussed properties of functions satisfying this condition. In 1992 Bector *et al.* [3] introduced the class of univex functions and obtained sufficient optimality conditions and duality results. Recently, Bector [1] defined properly  $(b, \eta)$ -invex functions and established a sufficient optimality theorem and duality results for a class of minimax programming problems. In this paper we generalize the results given in [1] to a new class of functions, called properly  $(b, \eta, \phi)$ -univex functions.

### 2. PRELIMINARIES

In this section we give some definitions, the main problem considered in the paper, and some results needed in the sequel.

We will distinguish between  $\leq$  and  $\leqslant$ , and between  $\geq$  and  $\geqslant$ . For  $x, y \in R^n$  we define  $x \leqslant y$  iff  $x_i \leqslant y_i$  for  $i = 1, 2, \dots, n$ ;  $x \leq y$  iff  $x \leqslant y$  and  $x \neq y$ ;  $x \geqslant y$  iff  $x_i \geqslant y_i$  for  $i = 1, 2, \dots, n$ ; and  $x \geq y$  iff  $x \geqslant y$  and  $x \neq y$ .

Let  $X \subseteq R^n$  be an open set. The next two definitions below are due to Hanson [4].

**Definition 2.1.** A differentiable function  $f : X \rightarrow R$  is said to be  $\eta$ -invex if there exists a function  $\eta : X \times X \rightarrow R^n$  such that for each  $x, u \in X$ ,

$$f(x) - f(u) \geq \eta(x, u)^T \nabla f(u).$$

**Definition 2.2.** A differentiable function  $f : X \rightarrow R$  is said to be *strictly*  $\eta$ -invex if there exists a function  $\eta : X \times X \rightarrow R^n$  such that for each  $x, u \in X$ ,

$$f(x) - f(u) > \eta(x, u)^T \nabla f(u).$$

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2000 *Mathematics Subject Classification.* 90C47, 90C46.

*Key words and phrases.* Minimax programming, duality, generalized convex functions.

\*The research of this author is financially supported by the University Grants Commission of India through grant No. F. 8 – 33/2001(SR – I)

The following definition is due to Bector [1].

**Definition 2.3.** A differentiable function  $f : X \rightarrow R$  is said to be *properly  $(b, \eta)$ -invex* if there exist functions  $\eta : X \times X \rightarrow R^n$  and  $b : X \times X \rightarrow R^+ \setminus \{0\}$  such that for each  $x, u \in X$ ,

$$b(x, u)[f(x) - f(u)] \geq \eta(x, u)^T \nabla f(u).$$

The concept of univexity was introduced by Bector et al.[3] in 1992.

**Definition 2.4.** A differentiable function  $f : X \rightarrow R$  is said to be *properly  $(b, \eta, \phi)$ -univex* if there exist functions  $\eta : X \times X \rightarrow R^n$ ,  $b : X \times X \rightarrow R^+ \setminus \{0\}$  and  $\phi : R \rightarrow R$ , such that for each  $x, u \in X$ ,

$$b(x, u)\phi[f(x) - f(u)] \geq \eta(x, u)^T \nabla f(u).$$

If  $\phi$  is the identity function, then the above definition reduces to the definition of  $(b, \eta)$ -invexity [1]. There exist functions that are properly  $(b, \eta, \phi)$ -univex, but they are not properly  $(b, \eta)$ -invex.

**Example 2.1.** Let  $f : [1, \infty) \rightarrow R$  defined by  $f(x) = -x + 1$ . This function is properly  $(b, \eta, \phi)$ -univex with respect to  $\eta(x, u) = -1/x + u$ ,  $b = 1$ ,  $\phi(x) = -x$  at  $u = 1$ , but it is not properly  $(b, \eta)$ -invex.

**Definition 2.5.** A differentiable function  $f : X \rightarrow R$  is said to be *properly strictly  $(b, \eta, \phi)$ -univex* if there exist functions  $\eta : X \times X \rightarrow R^n$ ,  $b : X \times X \rightarrow R^+ \setminus \{0\}$  and  $\phi : R \rightarrow R$ , such that for each  $x, u \in X$ ,

$$b(x, u)\phi[f(x) - f(u)] > \eta(x, u)^T \nabla f(u).$$

The following theorem, which we shall use in the sequel, is easy to prove; therefore we state it without proof. This theorem is an extension of Theorem 2.1 [1].

**Theorem 2.1.** Let  $f_i$  and each of  $h_{ij}$ ,  $j = 1, 2, \dots, m$ , be properly  $(b_i, \eta, \phi)$ -univex on  $X$ . If  $\lambda_i \geq 0$  and  $y_{ij} \geq 0$ ,  $j = 1, 2, \dots, m$ , then  $\lambda_i f_i + \sum_{j=1}^m y_{ij} h_{ij}$  is properly  $(b_i, \eta, \phi)$ -univex on  $X$ . If  $f_i$  is properly strictly  $(b_i, \eta, \phi)$ -univex and  $\lambda_i > 0$ , or at least one of  $h_{ij}$  for which the corresponding  $y_{ij} > 0$ , is properly strictly  $(b_i, \eta, \phi)$ -univex, then  $\lambda_i f_i + \sum_{j=1}^m y_{ij} h_{ij}$  is properly strictly  $(b_i, \eta, \phi)$ -univex on  $X$ .

**Primal problem.** In this paper we consider the following generalized minimax programming problem as the primal problem.

$$q^* = \min_{x \in X} \max_{1 \leq i \leq p} [f_i(x)],$$

subject to  $h_{ij}(x) \leq 0$ ,  $i = 1, 2, \dots, p$ ,  $j = 1, 2, \dots, m$ .

We assume that  $f_i$ ,  $i = 1, 2, \dots, p$ , and  $h_{ij}(x)$ ,  $i = 1, 2, \dots, p$ ;  $j = 1, 2, \dots, m$  are differentiable on  $X$ .

We now consider the following programming problem (E) which is equivalent to (P) in the sense of the Lemmas 2.1 and 2.2 given below.

$$\min_{x,q} q$$

subject to

$$\begin{aligned} (1) \quad & f_i(x) \leq q, \quad i = 1, 2, \dots, p \\ (2) \quad & h_{ij}(x) \leq 0, \quad i = 1, 2, \dots, p; \quad j = 1, 2, \dots, m, \\ & x \in X. \end{aligned}$$

**Lemma 2.1.** *Let  $x$  be (P)-feasible. Then there exists  $q \in R$  such that  $(x, q)$  is (E)-feasible, and if  $(x, q)$  is (E)-feasible, then  $x$  is (P)-feasible.*

**Lemma 2.2.** *Let  $x^*$  be (P)-optimal. Then there exists  $q^* \in R$  such that  $(x^*, q^*)$  is (E)-optimal, and if  $(x^*, q^*)$  is (E)-optimal then  $x^*$  is (P)-optimal with  $q^*$  as the optimal value of the (P)-objective.*

### 3. OPTIMALITY CONDITIONS

The Kuhn-Tucker conditions are necessary in the solution of a nonlinear programming problem if a constraint qualification is satisfied. Most of the constraint qualifications that appear in the literature do not involve the objective function. See Mangasarian [5] for several examples of constraint qualifications. One of them, known as Slater's, requires the set of feasible points to contain an interior point.

**Lemma 3.1** (Necessary optimality conditions [1]). *Let  $x^*$  be (P)-optimal. Let a constraint qualification hold for (P). Then there exist  $q^* \in R$ ,  $\lambda^* \in R^p$  and a matrix  $Y^* \in R^{p \times m}$ , such that  $(x^*, q^*, \lambda^*, Y^*)$  satisfies*

$$(3) \quad \sum_{i=1}^p \nabla[\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*)] = 0$$

$$(4) \quad \lambda_i^* [f_i(x^*) - q^*] = 0, \quad i = 1, 2, \dots, p,$$

$$(5) \quad y_{ij}^* h_{ij}(x^*) = 0, \quad i = 1, 2, \dots, p; \quad j = 1, 2, \dots, m,$$

$$(6) \quad f_i(x^*) \leq q^*, \quad i = 1, 2, \dots, p,$$

$$(7) \quad h_{ij}(x^*) \leq 0, \quad i = 1, 2, \dots, p; \quad j = 1, 2, \dots, m,$$

$$(8) \quad \sum_{i=1}^p \lambda_i^* = 1,$$

$$(9) \quad q^* \in R, \quad \lambda^* \in R^p, \quad Y^* \in R^{p \times m}, \quad \lambda^* \geq 0, \quad Y^* \geq 0.$$

**Theorem 3.1** (Sufficient optimality conditions). *If  $(x^*, q^*, \lambda^*, Y^*)$  satisfies (3)-(9),  $\phi$  is a linear mapping, and the following conditions are satisfied: Either (i) Each  $f_i$ ,  $i = 1, 2, \dots, p$ , and  $h_{ij}(x)$ ,  $i = 1, 2, \dots, p$ ,  $j = 1, 2, \dots, m$ , is a properly  $(b_i, \eta, \phi)$ -univex function on  $X$ ; or (ii)  $\lambda_i f_i + \sum_{j=1}^m y_{ij} h_{ij}$  is properly  $(b_i, \eta, \phi)$ -univex on  $X$  for  $i = 1, 2, \dots, p$ , and  $\lambda_i \geq 0$ ,  $y_{ij} \geq 0$ ,  $i = 1, 2, \dots, p$ ;  $j = 1, 2, \dots, m$ , and (iii)  $\phi(a) \geq 0 \Rightarrow a \geq 0$ , then  $x^*$  is (P)-optimal.*

*Proof.* First we prove that  $(x^*, q^*)$  is (E)-optimal. Since  $(x^*, q^*, \lambda^*, Y^*)$  satisfies (3), therefore we have

$$(10) \quad \eta(x, x^*)^T \sum_{i=1}^p \nabla[\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*)] = 0$$

for all (P)-feasible solutions  $x$ .

From Theorem 2.1 and either (i) or (ii),  $\lambda_i f_i + \sum_{j=1}^m y_{ij} h_{ij}$  is properly  $(b_i, \eta, \phi)$ -univex on  $X$ . Therefore,

$$(11) \quad b_i(x, x^*) \phi[(\lambda_i^* f_i(x) + \sum_{j=1}^m y_{ij}^* h_{ij}(x)) - (\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*))] \\ \geq \eta(x, x^*)^T \nabla[\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*)].$$

By taking summation over  $i$  in (11), we obtain

$$(12) \quad \sum_{i=1}^p b_i(x, x^*) \phi[(\lambda_i^* f_i(x) + \sum_{j=1}^m y_{ij}^* h_{ij}(x)) - (\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*))] \\ \geq \eta(x, x^*)^T \sum_{i=1}^p \nabla[\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*)].$$

Now (10) and (12) yield

$$\sum_{i=1}^p b_i(x, x^*) \phi[(\lambda_i^* f_i(x) + \sum_{j=1}^m y_{ij}^* h_{ij}(x)) - (\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*))] \geq 0.$$

From (iii) and the linearity of  $\phi$  we get

$$(13) \quad \sum_{i=1}^p b_i(x, x^*) [(\lambda_i^* f_i(x) + \sum_{j=1}^m y_{ij}^* h_{ij}(x)) - (\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*))] \geq 0.$$

Now multiplying both sides of (1) by  $\lambda_i^* \geq 0$ , we obtain

$$(14) \quad \lambda_i^* f_i(x) \leq \lambda_i^* q, \quad i = 1, 2, \dots, p.$$

Multiplying both sides of (2) by  $y_{ij}^*$  and summing over  $j = 1, 2, \dots, m$ , we obtain

$$(15) \quad \sum_{j=1}^m y_{ij}^* h_{ij}(x) \leq 0, \quad i = 1, 2, \dots, p.$$

Adding (14) and (15) we get

$$(16) \quad \lambda_i^* f_i(x) + \sum_{j=1}^m y_{ij}^* h_{ij}(x) \leq \lambda_i^* q.$$

Since  $(x^*, q^*, \lambda^*, Y^*)$  satisfies (4) and (5) we have

$$(17) \quad \lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*) = \lambda_i^* q^*.$$

Using (16) and (17) in (13) we obtain

$$(18) \quad (q - q^*) \left[ \sum_{i=1}^p b_i(x, x^*) \lambda_i^* \right] \geq 0.$$

Since  $\lambda_i^* \geq 0$ ,  $\sum_{i=1}^p \lambda_i^* = 1$ , and  $b_i(x, x^*) > 0$ ,  $i = 1, 2, \dots, p$ ,  $\sum_{i=1}^p b_i(x, x^*) \lambda_i^* > 0$ .

Hence, from (18), we have  $q \geq q^*$  for  $(x^*, q^*)$  and for all (E)-feasible points  $(x, q)$ . Thus  $(x^*, q^*)$  is (E)-optimal. Hence, by Lemma 2.2,  $x^*$  is (P)-optimal with  $q^*$  as the optimal value of the (P)-objective.  $\square$

The previous theorem is an extension of Theorem 3.2 [1].

#### 4. DUALITY THEOREMS

We now consider the following dual (D) to (E).

$$\text{Max } v$$

subject to

$$(19) \quad \sum_{i=1}^p \nabla [\lambda_i f_i(u) + \sum_{j=1}^m y_{ij} h_{ij}(u)] = 0$$

$$(20) \quad \lambda_i f_i(u) + \sum_{j=1}^m y_{ij} h_{ij}(u) \geq \lambda_i v, \quad i = 1, 2, \dots, p$$

$$(21) \quad \sum_{i=1}^p \lambda_i = 1,$$

$$(22) \quad u \in X, v \in R, \lambda \in R^p, Y \in R^{p \times m}, \lambda \geq 0, Y \geq 0.$$

We shall denote the set of (E)-feasible solutions by  $W$  and the set of (D)-feasible solutions by  $T$ .

**Theorem 4.1** (Weak duality). *If  $(x, q) \in W, (u, v, \lambda, Y) \in T, \phi$  is a linear mapping, and  $\phi(a) \geq 0 \Rightarrow a \geq 0$ , then  $q \geq v$ .*

*Proof.* If  $(x, q) \in W$  and  $(u, v, \lambda, Y) \in T$ , we have, from (19),

$$(23) \quad \eta(x, u)^T \sum_{i=1}^p \nabla[\lambda_i f_i(u) + \sum_{j=1}^m y_{ij} h_{ij}(u)] = 0.$$

Using Theorem 2.1 (as in Theorem 3.1) and (23), we obtain for  $(x, q) \in W$  and  $(u, v, \lambda, Y) \in T$ ,

$$\sum_{i=1}^p b_i(x, u) \phi[(\lambda_i f_i(x) + \sum_{j=1}^m y_{ij} h_{ij}(x)) - (\lambda_i f_i(u) + \sum_{j=1}^m y_{ij} h_{ij}(u))] \geq 0.$$

From the hypothesis on  $\phi$  and the linearity of this function we get

$$(24) \quad \sum_{i=1}^p b_i(x, u)[(\lambda_i f_i(x) + \sum_{j=1}^m y_{ij} h_{ij}(x)) - (\lambda_i f_i(u) + \sum_{j=1}^m y_{ij} h_{ij}(u))] \geq 0.$$

Now, using the constraints (1) and (2) of (E), and the constraints (20) and (22) in (24), we obtain for  $(x, q) \in W$  and  $(u, v, \lambda, Y) \in T$ ,

$$(q - v) \sum_{i=1}^p b_i(x, u) \lambda_i \geq 0.$$

Since  $\sum_{i=1}^p b_i(x, u) \lambda_i > 0$  it follows that  $q \geq v$  for  $(x, q) \in W$  and  $(u, v, \lambda, Y) \in T$ . □

The previous theorem is an extension of Theorem 4.1 [1].

**Corollary 4.1.** *For  $(x^*, q^*) \in W$  and  $(u^*, v^*, \lambda^*, Y^*) \in T$  let  $q^* = v^*$ . Then  $(x^*, q^*)$  is (E)-optimal and  $(u^*, v^*, \lambda^*, Y^*)$  is (D)-optimal.*

**Theorem 4.2** (Direct duality). *Let  $(x^*, q^*) \in W$ , at which a constraint qualification holds, be (E)-optimal. Then there exist  $\lambda^* \in R^p$  and  $Y^* \in R^{p \times m}$  such that  $(x^*, q^*, \lambda^*, Y^*) \in T$ , the (D)-objective value is equal to the (E)-objective value at  $(x^*, q^*, \lambda^*, Y^*)$ , and  $(x^*, q^*, \lambda^*, Y^*)$  is (D)-optimal.*

*Proof.* Since  $(x^*, q^*)$  is (E)-optimal, therefore there exist  $\lambda^* \in R^p$  and  $Y^* \in R^{p \times m}$  such that conditions (3)-(9) are satisfied at  $(x^*, q^*, \lambda^*, Y^*)$ . From (3)-(5), (8), and (9) it follows that  $(x^*, q^*, \lambda^*, Y^*)$  is (D)-feasible. The (D)-objective value is equal to  $q^*$ , which is the same as the (E)-objective. Using Corollary 4.1, we get that  $(x^*, q^*, \lambda^*, Y^*)$  is (D)-optimal. □

The following theorem is an extension of Theorem 4.3 [1].

**Theorem 4.3** (Strict converse duality). *Let  $(x^*, q^*) \in W$ , at which a constraint qualification holds. Let  $(x^*, q^*)$  be (E)-optimal, and let  $(u^*, v^*, \lambda^*, Y^*) \in T$  be (D)-optimal. Assume that  $\phi$  is a linear mapping, and for  $i = 1, 2, \dots, p$ , and for every (E)-feasible solution, at least one of the  $f_i$ , for which the corresponding  $\lambda_i > 0$ , is properly strictly  $(b_i, \eta, \phi)$ -univex, or at least one of the  $h_{ij}$ , for which the corresponding  $y_{ij} > 0$ , is properly strictly  $(b_i, \eta, \phi)$ -univex, then  $(x^*, q^*) = (u^*, v^*)$ .*

*Proof.* We assume that  $(x^*, q^*) \neq (u^*, v^*)$  and exhibit a contradiction. Since  $(x^*, q^*)$  is (E)-optimal, there exist  $\lambda^0 \in R^p$  and  $Y^0 \in R^{p \times m}$  such that  $(x^*, q^*, \lambda^0, Y^0) \in T$  and is (D)-optimal. Also  $(u^*, v^*, \lambda^*, Y^*) \in T$  is (D)-optimal, therefore,

$$(25) \quad q^* = v^*.$$

$$(26) \quad \eta(x^*, u^*)^T \sum_{i=1}^p \nabla[\lambda_i^* f_i(u^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(u^*)] = 0.$$

Similar to steps followed in the proof of Theorem 3.1, from (26) and Theorem 2.1, we get

$$(27) \quad \sum_{i=1}^p b_i(x^*, u^*) [(\lambda_i^* f_i(x^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(x^*)) - (\lambda_i^* f_i(u^*) + \sum_{j=1}^m y_{ij}^* h_{ij}(u^*))] > 0.$$

As in Theorem 3.1, (27) yields  $(q^* - v^*) \sum_{i=1}^p b_i(x^*, u^*) \lambda_i^* > 0$ . Since  $\sum_{i=1}^p b_i(x^*, u^*) \lambda_i^* > 0$  then  $q^* > v^*$ , which contradicts (25). Therefore  $(x^*, q^*) = (u^*, v^*)$ .  $\square$

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*Manuscript received June 26, 2002*

*revised March 9, 2006*

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