

Optimality Conditions for D.C. Vector Optimization Problems Under Reverse Convex Constraints

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Abstract. In this paper, we establish global necessary and sufficient optimality conditions for D.C. vector optimization problems under reverse convex constraints. An application to vector fractional mathematical programming is also given.

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1. Introduction

In very recent years, the analysis and applications of D.C. mappings (difference of convex mappings) have been of considerable interest [11, 18, 27, 31]. Generally, nonconvex mappings that arise in nonsmooth optimization are often of this type. Recently, extensive work on the analysis and optimization of D.C. mappings has been carried out [7, 8, 21]. However, much work remains to be done.

Reverse convex optimization, that is, minimizing an extended real-valued convex function subject to a reverse convex constraint, constitutes a general framework for a large class of nonconvex optimization problems including D.C. optimization (minimizing or maximizing a difference of two extended real-valued convex functions), maximizing a convex function over a convex set, and minimizing a convex function over a reverse convex set, i.e., the complement of a convex subset of a convex set. This subject has received increased attention in recent years mainly for numerical purposes [13, 28, 30], duality theory in D.C. optimization [15, 16, 23] or from the point of view of necessary and sufficient conditions for optimality with the use of subdifferential calculus of convex analysis and regularising techniques [6, 10, 11, 19, 20, 29].

In this paper, we are concerned with the multiobjective optimization problem

$$(P) \begin{cases} Y^+ - \text{Minimize } f(x) - g(x) \\ \text{subject to : } x \in X \setminus S \end{cases}$$

where X and Y are Banach spaces, $f, g: X \rightarrow Y$ are Y^+ -convex, proper and lower semi-continuous mappings, S is a nonempty open convex subset of X , and $Y^+ \subset Y$ is a pointed, convex and closed cone with nonempty interior. Our approach consists of using a special scalarization function introduced in optimization by Hiriart-Urruty [10] to detect necessary and sufficient optimality conditions for (P). Here, convex analysis theory plays a crucial role in our investigation.

Applying Corollary 3.3 and Theorem 3.4, we deduce optimality conditions for the special multiobjective optimization problem

$$\mathbb{R}_+^p - \text{Minimize } \left(\frac{f_1(x)}{g_1(x)}, \dots, \frac{f_p(x)}{g_p(x)} \right) \\ \text{subject to : } h(x) \notin -\text{int} Z^+$$

where $f_1, \dots, f_p, g_1, \dots, g_p: X \rightarrow \mathbb{R}$ are lower semicontinuous functions such that

$$f_i(x) \geq 0 \quad \text{and} \quad g_i(x) > 0 \quad \text{for all } i = 1, \dots, p$$

Z^+ is a nonempty closed convex cone and h is a Z^+ -convex mapping defined from X into another Banach space Z .

The rest of the paper is written as follows : Section 2 contains basic definitions and preliminary material. Section 3 is devoted to main results (optimality conditions). Section 4 discusses an application to vector fractional mathematical programming with reverse convex constraints.

2. Preliminaries

Throughout this paper, X, Y, Z and W are Banach spaces whose topological dual spaces are X^*, Y^*, Z^* and W^* , respectively. Let $Y^+ \subset Y$ (respectively $Z^+ \subset Z$) be a pointed ($Y^+ \cap (-Y^+) = \{0\}$), convex and closed cones ($\lambda Y^+ \subset Y^+$ for all $\lambda \geq 0$) with nonempty interior introducing a partial order in Y (respectively in Z) defined by

$$y_1 \leq_Y y_2 \Leftrightarrow y_2 \in y_1 + Y^+.$$

We adjoin to Y two artificial elements $+\infty$ and $-\infty$ such that

$$-\infty = -(+\infty), \quad y_1 - \infty \leq_Y y_2 \quad \text{for all } y_1, y_2 \in Y.$$

Moreover

$$y_2 \leq_Y y_1 + \infty = +\infty \quad \text{for all } y_1, y_2 \in Y \cup \{+\infty\}.$$

The negative polar cone Y° of Y^+ is defined as

$$Y^\circ = \{y^* \in Y^*: \langle y^*, y \rangle \leq 0 \quad \text{for all } y \in Y^+\}$$

where $\langle \cdot, \cdot \rangle$ is the dual pairs.

Since convexity plays an important role in the following investigations, recall the concept of cone-convex mappings.

The mapping $f: X \rightarrow Y \cup \{+\infty\}$ is said to be Y^+ -convex if for every $\alpha \in [0, 1]$ and $x_1, x_2 \in X$

$$\alpha f(x_1) + (1 - \alpha) f(x_2) \in f(\alpha x_1 + (1 - \alpha)x_2) + Y^+.$$

DEFINITION 2.1. A mapping $h: X \rightarrow Y \cup \{+\infty\}$ is said to be Y^+ -D.C. if there exists two Y^+ -convex mappings f and g such that

$$h(x) = f(x) - g(x) \quad \forall x \in X.$$

Let us recall the definition of the lower semicontinuity of a mapping. For more details on this concept, we refer the interested reader to [4, 22].

DEFINITION 2.2. [22] A mapping $f: X \rightarrow Y \cup \{+\infty\}$ is said to be lower semicontinuous at $\bar{x} \in X$, if for any neighborhood V of zero and for any $b \in Y$ satisfying $b \leq_Y f(\bar{x})$, there exists a neighborhood U of \bar{x} in X such that

$$f(U) \subset b + V + (Y^+ \cup \{+\infty\}).$$

DEFINITION 2.3. [24, 32] Let $f: X \rightarrow Y \cup \{+\infty\}$ be a Y^+ -convex mapping. The vectorial subdifferential of f at $\bar{x} \in \text{dom} f$ is given by

$$\partial^v f(\bar{x}) = \{T \in L(X, Y) : T(h) \leq_Y f(\bar{x} + h) - f(\bar{x}) \forall h \in X\}.$$

REMARK 2.1. When f is a convex function, $\partial^v f(\bar{x})$ reduces to the well-known subdifferential

$$\partial f(\bar{x}) = \partial_{A.C} f(\bar{x}) = \{x^* \in X^* : f(x) - f(\bar{x}) \geq \langle x^*, x - \bar{x} \rangle \quad \text{for all } x \in X\}.$$

REMARK 2.2. Let $f: X \rightarrow Y \cup \{+\infty\}$ be a Y^+ -convex mapping. If f is also continuous at \bar{x} , then

$$\partial^v f(\bar{x}) \neq \emptyset.$$

The next concept was introduced in [5] in finite dimension. We give it in the infinite case.

DEFINITION 2.4. Let U be a nonempty subset of Y . A functional $g: U \rightarrow \mathbb{R} \cup \{+\infty\}$ is called Y^+ -increasing on U , if for each $y_0 \in U$

$$y \in (y_0 + Y^+) \cap U \quad \text{implies} \quad g(y) \geq g(y_0).$$

In [14], and using the separation Hahn-Banach geometric theorem, B. Lemaire set the following proposition which generalize both Gol'shtein's result [9] and Levin's result [17]. He used, for a simple application $h: Y \rightarrow \mathbb{R} \cup \{+\infty\}$, and another application which is Y^+ -increasing $g: Y \rightarrow \mathbb{R} \cup \{+\infty\}$, the convention that

$$g \circ h(x) = g(h(x)) \quad \text{if} \quad h(x) \in \text{dom}(g) \quad \text{and} \quad g(+\infty) = +\infty.$$

Consequently, $g \circ h$ is an application from X into $\mathbb{R} \cup \{+\infty\}$ and its effective domain is given by

$$\text{dom}(g \circ h) = \text{dom}(h) \cap h^{-1} \text{dom}(g).$$

PROPOSITION 2.1. [14] *Let X and Y be two real Banach spaces. Consider a mapping h from X into $Y \cup \{+\infty\}$ and a function g from Y into $\mathbb{R} \cup \{+\infty\}$. If*

- (i) h is Y^+ -convex,
- (ii) g is convex, Y^+ -increasing and continuous in some point of $h(X)$.

Then

$$\partial(g \circ h)(x) = \bigcup_{y^* \in \partial g(h(x))} \partial(y^* \circ h)(x).$$

In the sequel, we shall need the following result of [4]. Under the nonemptiness of the set $\{x \in X: h(x) \in -\text{int } Y^+\}$, one has

$$\partial(\delta_{-Y^+} \circ h)(\bar{x}) = \bigcup_{\substack{y^* \in (-Y^+)^{\circ} \\ \langle y^*, h(\bar{x}) \rangle = 0}} \partial(y^* \circ h)(\bar{x}) \quad (2.1)$$

where the symbol $\langle \cdot, \cdot \rangle$ denotes the bilinear pairing between Y and Y^* , and δ_S is the indicator function of S .

REMARK 2.3. Notice that the function $y \rightarrow \delta_{-Y^+}(y)$ is Y^+ -increasing. Moreover for any Y_+ -convex mapping $h: X \rightarrow Y \cup \{+\infty\}$, the composite function $\delta_{-Y^+} \circ h$ is also convex.

For a subset A of Y , we consider the function

$$\Delta_A(y) = \begin{cases} d(y, A) & \text{if } y \in Y \setminus A \\ -d(y, Y \setminus A) & \text{if } y \in A \end{cases}$$

where $d(y, A) = \inf \{\|u - y\| : u \in A\}$. This function was introduced by Hiriart-Urruty [10] (see also [12]), and used after by Ciligot-Travain [2], and Amahroq and Taa [1].

The next proposition has been established by Hiriart-Urruty [10].

PROPOSITION 2.2. [10] *Let $A \subset Y$ be a pointed closed convex cone with nonempty interior and $A \neq Y$. The function Δ_A is convex, positively homogeneous, 1-Lipschitzian, decreasing on Y with respect to the order introduced by S . Moreover $(Y \setminus A) = \{y \in Y : \Delta_A(y) > 0\}$, $\text{int}(A) = \{y \in Y : \Delta_A(y) < 0\}$ and the boundary of A : $bd(A) = \{y \in Y : \Delta_A(y) = 0\}$.*

It is easy to verify the following lemma.

LEMMA 2.3. *The function $\Phi: Y \rightarrow \mathbb{R}$ defined by*

$$\Phi(y) = \Delta_{-\text{int}(Y^+)}(y)$$

is (Y^+) -increasing on Y .

Let K be a closed convex subset of X . The normal cone $N(K, \bar{x})$ to K at \bar{x} is denoted by

$$N(K, \bar{x}) = \{x^* \in X^* : 0 \geq \langle x^*, x - \bar{x} \rangle \text{ for all } x \in K\}.$$

This cone can be also written as

$$N(K, \bar{x}) = \partial \delta_K(\bar{x})$$

where δ_K is the indicator function of K . Properties of the subdifferential and the normal cone can be found in Rockafellar [25].

As a direct consequence of Proposition 2.2, one has the following result.

PROPOSITION 2.4. [2] *Let $A \subset Y$ be a closed convex cone with a nonempty interior. For all $y \in Y$, one has*

$$0 \notin \partial \Delta_S(y).$$

3. Optimality Conditions

We begin by giving necessary optimality condition for the optimization problem

$$(P_1): \begin{cases} Y^+ - \text{Minimize } f(x) - g(x) \\ \text{subject to: } & x \in C, \end{cases}$$

where $f, g: X \rightarrow Y \cup \{+\infty\}$ are convex and lower semi-continuous mappings and C a closed set.

The point $\bar{x} \in C$ is an efficient (respectively weak efficient) solution of (P_1) if $(f - g)(\bar{x})$ is a Pareto (respectively weak Pareto) minimal vector of $(f - g)(C)$.

For all the sequel, we assume that $\bar{x} \in \text{dom}(f) \cap \text{dom}(g)$.

LEMMA 3.1. *If $\bar{x} \in C$ is a weak minimal solution of (P_1) with respect to Y^+ , then for all $T \in \partial^v g(\bar{x})$, \bar{x} solves the following scalar convex minimization problem*

$$(P_2) \begin{cases} \text{Minimize } \Delta_{-\text{int}(Y^+)}(f(x) - f(\bar{x}) - T(x - \bar{x})) \\ \text{Subject to } x \in C. \end{cases}$$

Proof. Suppose the contrary. There exist $x_0 \in C$ such that

$$\Delta_{-\text{int}(Y^+)}(f(x_0) - f(\bar{x}) - T(x_0 - \bar{x})) < \Delta_{-\text{int}(Y^+)}(0) = 0.$$

This implies with Proposition 2.4 that

$$f(x_0) - f(\bar{x}) - T(x_0 - \bar{x}) \in -\text{int}(Y^+). \quad (3.1)$$

By assumption, since $T \in \partial^v g(\bar{x})$, one has

$$\langle T, x_0 - \bar{x} \rangle \in -(g(x_0) - g(\bar{x})) - Y^+ \quad (3.2)$$

From (3.1), (3.2) and the fact that $\text{int}(Y^+) + Y^+ \subset \text{int}(Y^+)$, we obtain

$$f(x_0) - g(x_0) - (f(\bar{x}) - g(\bar{x})) \in -\text{int}(Y^+)$$

which contradicts the fact that \bar{x} is a weak minimal solution of (P_1) . \square

THEOREM 3.2. *Assume that f is finite and continuous at \bar{x} . If \bar{x} is a weak minimal solution of (P_1) then for all $T \in \partial^v g(\bar{x})$ there exist $y^* \in (-Y^+)^\circ \setminus \{0\}$ such that*

$$y^* \circ T \in \partial (y^* \circ f)(\bar{x}) + N^c(C, \bar{x}).$$

Here, $N^c(C, x)$ designates the Clarke normal cone to C at x .

Proof. Set $H(\cdot) = f(\cdot) - f(\bar{x}) - T(\cdot - \bar{x})$.

- On the one hand, as $\Delta_{-\text{int}(Y^+)}$ is Y^+ -increasing and H is Y^+ -convex, then $\Delta_{-\text{int}(Y^+)} \circ H$ is convex.
- On the second hand, as $\Delta_{-\text{int}(Y^+)}$ and H is continuous, then $\Delta_{-\text{int}(Y^+)} \circ H$ is continuous.

Consequently, $\Delta_{-\text{int}(Y^+)} \circ H$ is locally Lipschitzian. Denoting by $k_0 > 0$ the Lipschitz constant of $\Delta_{-\text{int}(Y^+)} \circ H$, due to the Clarke penalization [3], there exists $k \geq k_0$ such that

$$0 \in \partial^c (\Delta_{-\text{int}(Y^+)}(H(\cdot)) + kd_C)(\bar{x}).$$

Applying the sum rule [3], we obtain

$$0 \in \partial^c (\Delta_{-\text{int}(Y^+)}(H(\cdot)))(\bar{x}) + k\partial^c d(\cdot, C).$$

Since H is Y^+ -convex and $\Delta_{-\text{int}(Y^+ \times Z^+)}(\cdot)$ is convex continuous in 0 and Y^+ -increasing, due to Proposition 2.1, there exist $y^* \in \partial \Delta_{-\text{int}(Y^+)}(0)$ such that

$$0 \in \partial (y^* \circ H)(\bar{x}) + N^c(C, \bar{x}).$$

Since $\Delta_{-\text{int}(Y^+)}(\cdot)$ is a convex function and $\Delta_{-\text{int}(Y^+)}(0) = 0$ we have for all $y \in Y$

$$\Delta_{-\text{int}(Y^+)}(y) \geq \langle y^*, y \rangle$$

and hence for all $y \in -Y^+$

$$\langle y^*, y \rangle \leq \Delta_{-\text{int}(Y^+)}(y) = -d(y, Y \setminus -\text{Int}(Y^+)) \leq 0.$$

That is $y^* \in (-Y^+)^\circ$. We conclude from Proposition 2.4 that $y^* \neq 0$.

Consequently, there exist $y^* \in (-Y^+)^\circ \setminus \{0\}$ satisfying

$$0 \in \partial (y^* \circ f + \langle -y^* \circ T, x - \bar{x} \rangle)(\bar{x}) + N^c(C, \bar{x}).$$

Finally, for all $T \in \partial^v g(\bar{x})$, there exist $y^* \in (-Y^+)^\circ \setminus \{0\}$ such that

$$y^* \circ T \in \partial(y^* \circ f)(\bar{x}) + N^c(C, \bar{x}). \quad \square$$

Let S be a nonempty open convex subset of X . Setting $C := X \setminus S$, one has Theorem 3.3 which gives necessary optimality conditions for the reverse optimization problem (P) .

THEOREM 3.3. *Assume that f is finite and continuous at \bar{x} and that \bar{x} is a weak minimal solution of (P) . Then, for all $T \in \partial^v g(\bar{x})$ there exist $y^* \in (-Y^+)^\circ \setminus \{0\}$ such that*

$$y^* \circ T \in \partial(y^* \circ f)(\bar{x}) - N(S, \bar{x}).$$

Proof. Let $T \in \partial^v g(\bar{x})$. Applying Theorem 3.2, there exist $y^* \in (-Y^+)^\circ \setminus \{0\}$ such that

$$y^* \circ T \in \partial(y^* \circ f)(\bar{x}) + N^c(C, \bar{x}). \quad (3.3)$$

Since S is an open convex subset, it is also epi-Lipschitzian at \bar{x} [26]. By a result of Rockafellar [26], we conclude that

$$N^c(X \setminus S, \bar{x}) = -N(S, \bar{x}). \quad (3.4)$$

Combining (3.3) and (3.4), we get the result. \square

REMARK 3.1. In Theorem 3.3, if \bar{x} is an interior point of S , then for all $T \in \partial^v g(\bar{x})$ there exist $y^* \in (-Y^+)^\circ \setminus \{0\}$ such that

$$y^* \circ T \in \partial(y^* \circ f)(\bar{x}).$$

THEOREM 3.4. *Suppose that $f, g: X \rightarrow Y \cup \{+\infty\}$ are convex, proper and lower semicontinuous, S is a nonempty open convex subset of X and $\bar{x} \in \text{dom} f \cap \text{dom} g$ is a boundary point of S . If there exists $y^* \in (-Y^+)^\circ \setminus \{0\}$ such that*

$$\partial_\varepsilon(y^* \circ g)(\bar{x}) + N(S, \bar{x}) \subset \partial_\varepsilon(y^* \circ f)(\bar{x}) \quad \text{for all } \varepsilon > 0. \quad (3.5)$$

Then \bar{x} is a weak minimal solution of (P_1) .

Proof. As in Theorem 3.3,

$$N^c(X \setminus S, \bar{x}) = -N(S, \bar{x}).$$

Since $\partial^c d(\cdot, X \setminus S)(\bar{x}) \subset N^c(X \setminus S, \bar{x})$, inclusion (3.5) becomes

$$\partial_\varepsilon(y^* \circ g)(\bar{x}) - \partial^c d(\cdot, X \setminus S)(\bar{x}) \subset \partial_\varepsilon(y^* \circ f)(\bar{x}), \quad \text{for all } \varepsilon > 0.$$

Consequently, for all $\varepsilon > 0$

$$\partial_\varepsilon(y^* \circ g)(\bar{x}) + \partial d(\cdot, S)(\bar{x}) - \partial^c d(\cdot, X \setminus S)(\bar{x}) \subset \partial_\varepsilon(y^* \circ f)(\bar{x}) + \partial d(\cdot, S)(\bar{x}).$$

As $\partial \Delta_S(\bar{x}) \subset \partial d(\cdot, S)(\bar{x}) - \partial^c d(\cdot, X \setminus S)(\bar{x})$, we get

$$\partial_\varepsilon(y^* \circ g)(\bar{x}) + \partial \Delta_S(\bar{x}) \subset \partial_\varepsilon(y^* \circ f)(\bar{x}) + \partial d(\cdot, S)(\bar{x}) \quad \text{for all } \varepsilon > 0$$

which yields that

$$\partial_\varepsilon(y^* \circ g)(\bar{x}) + \partial \Delta_S(\bar{x}) \subset \partial_\varepsilon(y^* \circ f + d(\cdot, S))(\bar{x}) \quad \text{for all } \varepsilon > 0. \quad (3.6)$$

Since Δ_S is convex continuous, one has

$$\partial_\varepsilon(y^* \circ g + \Delta_S)(\bar{x}) = \partial_\varepsilon(y^* \circ g)(\bar{x}) + \partial \Delta_S(\bar{x}) \quad \text{for all } \varepsilon > 0. \quad (3.7)$$

From (3.6) and (3.7), we obtain

$$\partial_\varepsilon(y^* \circ g + \Delta_S)(\bar{x}) \subset \partial_\varepsilon(y^* \circ f + d(\cdot, S))(\bar{x}) \quad \text{for all } \varepsilon > 0.$$

By the classical Hiriart-Urruty [11] sufficient conditions, \bar{x} minimize the function

$$y^* \circ f(x) - y^* \circ g(x) + d(x, X \setminus S).$$

We conclude that \bar{x} (a boundary point of S) is a minimum of the problem

$$\begin{aligned} &\text{Minimize } y^* \circ (f(x) - g(x)) \\ &\text{subject to : } x \in X \setminus S. \end{aligned}$$

Finally, due to $y^* \in (-Y^+)^\circ \setminus \{0\}$, \bar{x} is a weak minimal solution of (P_1) . \square

4. Application

In this section, we give an application to vector fractional mathematical programming under reverse convex constraints. Let $f_1, \dots, f_p, g_1, \dots, g_p: X \rightarrow \mathbb{R}$ be convex and lower semicontinuous functions such that

$$f_i(x) \geq 0 \text{ and } g_i(x) > 0 \text{ for all } i = 1, \dots, p.$$

We denote by ϕ the mapping defined as follows:

$$\phi(x) := \left(\frac{f_1(x)}{g_1(x)}, \dots, \frac{f_p(x)}{g_p(x)} \right).$$

We investigate the vector optimization problem

$$(P^*): \begin{cases} \mathbb{R}_+^p - \text{Minimize } \phi(x) \\ \text{subject to : } h(x) \notin -\text{int}Z^+ \end{cases}$$

where Z^+ is a nonempty closed convex cone and h is a Z^+ -convex mapping defined from X into Z .

Setting $S := \{x \in X : h(x) \in -\text{int}Z^+\}$, we assume that $S \neq \emptyset$ and $X \setminus S \neq \emptyset$. Then we have the following results.

LEMMA 4.1. *Let \bar{x} be a feasible point of problem (P^*) . \bar{x} is a weak minimal solution of (P^*) if and only if \bar{x} is a weak minimal solution of the following problem*

$$(P'') : \begin{cases} \mathbb{R}_+^p - \text{Minimize } (f_1(x) - \phi_1(\bar{x})g_1(x), \dots, f_p(x) - \phi_p(\bar{x})g_p(x)) \\ \text{subject to : } x \in X \setminus S \end{cases}$$

where $\phi_i(\bar{x}) = (f_i(\bar{x})) / (g_i(\bar{x}))$.

Proof. Let \bar{x} be a weak minimal solution of (P^*) . If there exists $x_1 \in \bar{x} + \mathbb{B}_X$ such that $x_1 \in X \setminus S$ and

$$(f_i(x_1) - \phi_i(\bar{x})g_i(x_1)) - (f_i(\bar{x}) - \phi_i(\bar{x})g_i(\bar{x})) \in -\text{Int}(\mathbb{R}_+^p).$$

Since $f_i(\bar{x}) - \phi_i(\bar{x})g_i(\bar{x}) = 0$, one has

$$\frac{f_i(x_1)}{g_i(x_1)} - \frac{f_i(\bar{x})}{g_i(\bar{x})} \in -\text{Int}(\mathbb{R}_+^p)$$

which contradicts the fact that \bar{x} is a weak minimal solution of (P^*) . So \bar{x} is a weak minimal solution of (P'') . The converse implication can be proved in a similar way. The proof is thus completed. \square

LEMMA 4.2. Denoting by \bar{S} the closure in X of the subset S , we have

$$\bar{S} := \{x \in X : h(x) \in -Z^+\}.$$

Proof. From the continuity assumption of h and the fact that the cone Y^+ is closed

$$\bar{S} \subset \{x \in X : h(x) \in -Z^+\}.$$

Conversely, let $x \in X$ such that $h(x) \in -Z^+$. From the nonemptiness of S , there exists $a \in X$ such that

$$h(a) \in -\text{int}(Z^+).$$

Setting $x_n := (1/n)a + (1 - (1/n))x$ for any $n \geq 1$, the sequence $(x_n)_{n \geq 1}$ converges to x .

Since h is convex, one has

$$h(x_n) \in \frac{1}{n}h(a) + \left(1 - \frac{1}{n}\right)h(x) - Z^+ \in -\text{int}(Z^+) - Z^+ \subset -\text{int}(Z^+);$$

which means that $x_n \in S$. Then,

$$\{x \in X : h(x) \in -Z^+\} \subset \bar{S}.$$

Finally, the desired equality holds. \square

THEOREM 4.3. Let \bar{x} be a boundary point of S and assume that f is finite and continuous at \bar{x} . If \bar{x} is a weak minimal solution of (P^*) , then for all $(T_1, \dots, T_p) \in \partial g_1(\bar{x}) \times \dots \times \partial g_p(\bar{x})$ there exist $(\alpha_1^*, \dots, \alpha_p^*) \in \mathbb{R}_+^p \setminus \{0\}$ and $z^* \in (-Z^+)^\circ$ such that $\langle z^*, h(\bar{x}) \rangle = 0$ and

$$\sum_{i=1}^p \phi_i(\bar{x}) \alpha_i^* T_i \in \partial \left(\sum_{i=1}^p \alpha_i^* f_i \right) (\bar{x}) - \partial (z^* \circ h) (\bar{x}).$$

Proof. Let $(T_1, \dots, T_p) \in \partial g_1(\bar{x}) \times \dots \times \partial g_p(\bar{x})$. Applying Lemma 4.1 and Theorem 3.3, there exist $(\alpha_1^*, \dots, \alpha_p^*) \in \mathbb{R}_+^p \setminus \{0\}$ and $z^* \in (-Z^+)^\circ$ such that $\langle z^*, h(\bar{x}) \rangle = 0$ and

$$\sum_{i=1}^p \phi_i(\bar{x}) \alpha_i^* T_i \in \partial \left(\sum_{i=1}^p \alpha_i^* f_i \right) (\bar{x}) - N(S, \bar{x}). \quad (4.1)$$

Using Lemma 4.2,

$$\delta_{\bar{S}} = \delta_{-Z^+} \circ h.$$

Since $N(S, \bar{x}) = N(\bar{S}, \bar{x})$, one obtains

$$N(S, \bar{x}) = \partial \delta_{\bar{S}}(\bar{x}) = \partial(\delta_{-Z^+} \circ h)(\bar{x}). \quad (4.2)$$

Combining (2.1), (4.1) and (4.2), we get the result. \square

THEOREM 4.4. *Suppose that $f, g: X \rightarrow Y \cup \{+\infty\}$ are convex, proper and lower semicontinuous, S is a nonempty open convex subset of X and $\bar{x} \in \text{dom } f \cap \text{dom } g$ is a boundary point of S . Suppose also that there exists $(\alpha_1^*, \dots, \alpha_p^*) \in \mathbb{R}_+^p \setminus \{0\}$ such that for any $z^* \in (-Z^+)^\circ$ one has $\langle z^*, h(\bar{x}) \rangle = 0$ and*

$$\partial_\varepsilon \left(\sum_{i=1}^p \phi_i(\bar{x}) \alpha_i^* g_i \right) (\bar{x}) + \partial(z^* \circ h)(\bar{x}) \subset \partial_\varepsilon \left(\sum_{i=1}^p \alpha_i^* f_i \right) (\bar{x}) \quad \text{for all } \varepsilon > 0. \quad (4.3)$$

Then, \bar{x} is a weak minimal solution of (P^*) .

Proof. As previously,

$$N_S(\bar{x}) = \partial \delta_{\bar{S}}(\bar{x}) = \partial(\delta_{-Z^+} \circ h)(\bar{x}) = \bigcup_{\substack{z^* \in (-Z^+)^\circ \\ \langle z^*, h(\bar{x}) \rangle = 0}} \partial(z^* \circ h)(\bar{x}).$$

Consequently, from inclusion (4.3), one has

$$\partial_\varepsilon \left(\sum_{i=1}^p \phi_i(\bar{x}) \alpha_i^* g_i \right) (\bar{x}) + N_S(\bar{x}) \subset \partial_\varepsilon \left(\sum_{i=1}^p \alpha_i^* f_i \right) (\bar{x}) \quad \text{for all } \varepsilon > 0.$$

Finally, applying Theorem 3.4, we finish the proof. \square

EXAMPLE 4.1. Let f and $g: \mathbb{R} \rightarrow \mathbb{R}$ be given functionals with

$$f(x) = |x| \quad \text{and} \quad g(x) = \frac{1}{2}x^2.$$

We consider $h: \mathbb{R} \rightarrow \mathbb{R}$ defined by

$$h(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0. \end{cases}$$

In this case, $\partial_\varepsilon g(0) = \{0\}$, $\partial_\varepsilon f(0) = [-1 - \varepsilon, 1 + \varepsilon]$ and $\partial h(0) = [0, 1]$. Under these assumptions, we remark that (4.3) is satisfied.

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