

Generalized (Φ, ρ) -convexity in nonsmooth vector optimization over cones

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(Received February 6, 2015; in final form January 17, 2016)

Abstract. In this paper, new classes of cone-generalized (Φ, ρ) -convex functions are introduced for a nonsmooth vector optimization problem over cones, which subsume several known studied classes. Using these generalized functions, various sufficient Karush-Kuhn-Tucker (KKT) type nonsmooth optimality conditions are established wherein Clarke's generalized gradient is used. Further, we prove duality results for both Wolfe and Mond-Weir type duals under various types of cone-generalized (Φ, ρ) -convexity assumptions.

Keywords: Nonsmooth vector optimization over cones; cone-generalized (Φ, ρ) -convexity; nonsmooth optimality conditions; duality.

AMS Classification: 90C26, 90C29, 90C46.

1. Introduction

Convexity plays an important role in many aspects of optimization theory including sufficient optimality conditions and duality theorems. In a quest to weaken the convexity hypothesis various generalized convexity notions have been introduced. Hanson and Mond [8] introduced F -convexity and Vial [10] defined ρ -convexity. Preda [9] unified the two concepts and gave the notion of an (F, ρ) -convex function.

Another generalization of convexity is invexity, introduced by Hanson [7]. The concept of (Φ, ρ) -invexity has been introduced by Caristi et al. [3]. Sufficient optimality conditions and duality results have been studied under (Φ, ρ) -invexity for differentiable single-objective and multiobjective programs [3,6]. (Φ, ρ) -invexity notion has been extended to the nonsmooth case

by Antczak and Stasiak [2].

In this paper, we use the concept of cones to define new classes of nonsmooth functions that we call K -generalized (Φ, ρ) -convex, K -generalized (Φ, ρ) -pseudoconvex and K -generalized (Φ, ρ) -quasiconvex functions, where K is a closed convex pointed cone with nonempty interior. Sufficient optimality conditions are proved for a nonsmooth vector optimization problem over cones using the above defined functions. Further, both Wolfe and Mond-Weir type duals are formulated and weak and strong duality results are established.

2. Definitions and preliminaries

Let S be a nonempty open subset of \mathbf{R}^n .

Definition 2.1. A function $\theta: S \rightarrow \mathbf{R}$ is said to be locally Lipschitz at a point $u \in S$ if for some $l_u > 0$,

$$|\theta(x) - \theta(\bar{x})| \leq l_u \|x - \bar{x}\|$$

for all x, \bar{x} in a neighborhood of u . We say that $\theta: S \rightarrow \mathbf{R}$ is locally Lipschitz on S if it is locally Lipschitz at each point of S .

Let $f = (f_1, f_2, \dots, f_m)^t: S \rightarrow \mathbf{R}^m$ be a vector-valued function. Then f is said to be locally Lipschitz on S if each f_i is locally Lipschitz on S .

Definition 2.2. [4] Let $\theta: S \rightarrow \mathbf{R}$ be a locally Lipschitz function on S . The Clarke's generalized directional derivative of θ at $u \in S$ in the direction v , denoted as $\theta^0(u; v)$, is defined by

$$\theta^0(u; v) = \limsup_{\substack{y \rightarrow u \\ t \rightarrow 0^+}} \frac{\theta(y + tv) - \theta(y)}{t}$$

Definition 2.3. [4] The Clarke's generalized gradient of θ at $u \in S$, denoted as $\partial\theta(u)$, is given by

$$\partial\theta(u) = \{ \xi \in \mathbf{R}^n : \theta^0(u; v) \geq \langle \xi, v \rangle, \forall v \in \mathbf{R}^n \}.$$

The generalized directional derivative of a locally Lipschitz function $f = (f_1, \dots, f_m)^t: S \rightarrow \mathbf{R}^m$ at $u \in S$ in the direction v is given by

$$f^0(u; v) = (f_1^0(u; v), f_2^0(u; v), \dots, f_m^0(u; v))^t.$$

The generalized gradient of f at u is the set $\partial f(u) = \partial f_1(u) \times \partial f_2(u) \times \dots \times \partial f_m(u)$, where $\partial f_i(u)$ is the generalized gradient of f_i at u for $i = 1, 2, \dots, m$. An element $A = (A_1, \dots, A_m)^t \in \partial f(u)$ is a continuous linear operator from \mathbf{R}^n to \mathbf{R}^m and

$$Au = (A_1^t u, \dots, A_m^t u)^t \in \mathbf{R}^m \text{ for all } u \in \mathbf{R}^n.$$

Let $K \subseteq \mathbf{R}^m$ be a closed convex pointed cone with nonempty interior and let $\text{int}K$ denote the interior of K . The positive dual cone K^* and the strict positive dual cone K^{s^*} of K , are respectively defined as

$$K^* = \{ y^* \in \mathbf{R}^m : \langle y, y^* \rangle \geq 0 \text{ for all } y \in K \}, \text{ and}$$

$$K^{s^*} = \{ y^* \in \mathbf{R}^m : \langle y, y^* \rangle > 0 \text{ for all } y \in K \setminus \{0\} \}.$$

Throughout the paper, we shall denote an element of \mathbf{R}^{n+1} by the ordered pair (a, r) , where $a \in \mathbf{R}^n$ and $r \in \mathbf{R}$. Consider a function $\varphi: S \times S \times \mathbf{R}^{n+1} \rightarrow \mathbf{R}$ such that $\varphi(x, u; \cdot)$ is convex on \mathbf{R}^{n+1} and $\varphi(x, u; (0, r)) \geq 0$ for every $x, u \in S$ and any real number $r \in \mathbf{R}_+$. Let $f: S \rightarrow \mathbf{R}^m$ be a locally Lipschitz function, $u \in S$,

$A = (A_1, \dots, A_m)^t \in \partial f(u)$, $\rho = (\rho_1, \dots, \rho_m)^t \in \mathbf{R}^m$ and $\Phi(x, u; (A, \rho))$ denote the vector $(\varphi(x, u; (A_1, \rho_1)), \dots, \varphi(x, u; (A_m, \rho_m)))^t$.

We introduce the following definitions:

Definition 2.4. The function f is said to be K -generalized (Φ, ρ) -convex at u on S if for every $x \in S$

$$f(x) - f(u) - \Phi(x, u; (A, \rho)) \in K, \quad \forall A \in \partial f(u).$$

Definition 2.5. The function f is said to be K -generalized (Φ, ρ) -pseudoconvex at u on S if for every $x \in S$, $A \in \partial f(u)$

$$-\Phi(x, u; (A, \rho)) \notin \text{int} K \Rightarrow -(f(x) - f(u)) \notin \text{int} K.$$

Equivalently, if for every $x \in S$

$$f(x) - f(u) \in -\text{int} K \Rightarrow \Phi(x, u; (A, \rho)) \in -\text{int} K, \\ \forall A \in \partial f(u).$$

Definition 2.6. The function f is said to be K -generalized (Φ, ρ) -quasiconvex at u on S if for every $x \in S$

$$f(x) - f(u) \notin \text{int} K \Rightarrow -\Phi(x, u; (A, \rho)) \in K, \\ \forall A \in \partial f(u).$$

If f is K -generalized (Φ, ρ) -convex (K -generalized (Φ, ρ) -pseudoconvex, K -generalized (Φ, ρ) -quasiconvex) at every $u \in S$ then f is said to be K -generalized (Φ, ρ) -convex (K -generalized (Φ, ρ) -pseudoconvex, K -generalized (Φ, ρ) -quasiconvex) on S .

Remark 2.7: 1) If $K = \mathbf{R}_+^m$ and $\varphi: S \times S \times \mathbf{R}^{n+1} \rightarrow \mathbf{R}$ is of the form

$$\varphi(x, u; (A, \rho)) = F(x, u, A) + \rho d(x, u)$$

where $F(x, u, \cdot)$ is sublinear, ρ is a constant and $d: S \times S \rightarrow \mathbf{R}_+$, then K -generalized (Φ, ρ) -convexity reduces to (F, ρ) -convexity introduced by Preda [9].

2) If f is a scalar valued function and $K = \mathbf{R}_+$, then Definition 2.4 becomes the definition of (Φ, ρ) -invexity given by Antczak and Stasiak [2].

3) If f is a differentiable function and $K = \mathbf{R}_+^m$, then the above definitions reduce to the corresponding definitions introduced in [6].

4) If $K = \mathbf{R}_+^m$ then Definition 2.4 becomes the definition of (Φ, ρ) -invexity introduced by Antczak [1].

Now we give an example of a K -generalized (Φ, ρ) -convex function.

Example 2.8. Let $S = \mathbf{R}^2$ and $K = \{(x, y) : x \leq 0, y \geq x\}$. Consider the following nonsmooth function $f : S \rightarrow \mathbf{R}^2$,

$$f(x) = (f_1(x), f_2(x)).$$

$$f_1(x_1, x_2) = \begin{cases} -x_1, & x_1 \geq 0 \\ 2x_1x_2, & x_1 < 0 \end{cases}$$

$$f_2(x_1, x_2) = \begin{cases} \frac{1}{2}x_1 + \frac{1}{3}x_2^4, & x_1 \geq 0 \\ x_1^2 + x_2^2, & x_1 < 0 \end{cases}$$

Here,

$$\partial f_1(0, 0) = (A_{11}, A_{12}), A_{11} \in [-1, 0], A_{12} \in \{0\}$$

and $\partial f_2(0, 0) = (A_{21}, A_{22}), A_{21} \in [0, \frac{1}{2}], A_{22} \in \{0\}$.

Define $\varphi : S \times S \times \mathbf{R}^3 \rightarrow \mathbf{R}$ as

$$\varphi(x, u; (a, \rho)) = \begin{cases} (x_1 + x_2^4)\rho, & x_1 \geq 0 \\ (x_1^2 + x_2^2)e^{-(a_1+a_2)}, & x_1 < 0 \end{cases}$$

Note that $\varphi(x, u; (., .))$ is convex on \mathbf{R}^3 , $\varphi(x, u; (0, r)) \geq 0$, for every $(x, u) \in S \times S$ and any $r \in \mathbf{R}_+$.

Set $\rho = (0, \frac{1}{3})$. Then, at $u = (0, 0)$ we have

$$f(x) - f(u) - \Phi(x, u; (A, \rho)) = \begin{cases} (-x_1, \frac{1}{6}x_1), & x_1 \geq 0 \\ (2x_1x_2 - (x_1^2 + x_2^2)e^{-(A_{11}+A_{12})}, \\ (x_1^2 + x_2^2)(1 - e^{-(A_{21}+A_{22})}), & x_1 < 0 \end{cases}$$

which gives that,

$$f(x) - f(u) - \Phi(x, u; (A, \rho)) \in K, \text{ for every } x \in S \text{ and } A \in \partial f(0, 0).$$

Hence, f is K -generalized (Φ, ρ) -convex at u on S .

It is clear that every K -generalized (Φ, ρ) -convex function is K -generalized (Φ, ρ) -pseudoconvex. Converse of this statement may not be true as shown by the following example.

Example 2.9. Let $S = \mathbf{R}^2$ and $K = \{(x, y) : x \geq 0, y \geq x\}$. Consider the following

nonsmooth function $f : S \rightarrow \mathbf{R}^2$,

$$f(x) = (f_1(x), f_2(x)).$$

$$f_1(x_1, x_2) = \begin{cases} -x_1, & x_1 \geq 0 \\ 0, & x_1 < 0 \end{cases}$$

$$f_2(x_1, x_2) = \begin{cases} -x_1 - 2x_2, & x_1 \geq 0 \\ x_1^2 + x_2^2, & x_1 < 0 \end{cases}$$

Here,

$$\partial f_1(0, 0) = (A_{11}, A_{12}), A_{11} \in [-1, 0], A_{12} \in \{0\}$$

and $\partial f_2(0, 0) = (A_{21}, A_{22}), A_{21} \in [-1, 0], A_{22} \in [-2, 0]$.

Define $\varphi : S \times S \times \mathbf{R}^3 \rightarrow \mathbf{R}$ as

$$\varphi(x, u; (a, \rho)) = \begin{cases} (x_1 + x_2^2)\rho, & x_1 \geq 0 \\ (x_1^2 + x_2^2)e^{a_1+a_2}, & x_1 < 0 \end{cases}$$

Note that, $\varphi(x, u; (., .))$ is convex on \mathbf{R}^3 , $\varphi(x, u; (0, r)) \geq 0$, for every $(x, u) \in S \times S$ and any $r \in \mathbf{R}_+$.

Set $\rho = (-\frac{1}{2}, -1)$. Then, at $u = (0, 0)$ we have

$$f(x) - f(u) \in -\text{int } K \Rightarrow x_1 > 0, x_2 > 0$$

$$\Rightarrow \Phi(x, u; (A, \rho)) \in -\text{int } K,$$

for every $x \in S$ and $A \in \partial f(0, 0)$.

Thus f is K -generalized (Φ, ρ) -pseudoconvex at u on S . But f fails to be K -generalized (Φ, ρ) -convex at u on S because for $x = (4, 1)$,

$$f(x) - f(u) - \Phi(x, u; (A, \rho)) = \left(-\frac{3}{2}, -1\right) \notin K.$$

3. Optimality conditions

Consider the following nonsmooth vector optimization problem over cones.

$$(NVOP) \quad K\text{-minimize } f(x)$$

$$\text{subject to } -g(x) \in Q,$$

where $f : S \rightarrow \mathbf{R}^m$, $g : S \rightarrow \mathbf{R}^p$ are locally Lipschitz vector-valued functions and S is a nonempty open subset of \mathbf{R}^n . K and Q are closed convex pointed cones with nonempty interiors in \mathbf{R}^m and \mathbf{R}^p respectively.

Let $S_0 = \{x \in S : -g(x) \in Q\}$ denote the set of feasible solutions of (NVOP).

Definition 3.1. A point $\bar{x} \in S_0$ is said to be

(i) a weak minimum of (NVOP) if for every $x \in S_0$

$$f(x) - f(\bar{x}) \notin -\text{int } K.$$

(ii) a minimum of (NVOP) if for every $x \in S_0$

$$f(x) - f(\bar{x}) \notin -K \setminus \{0\}.$$

The following constraint qualification and Karush-Kuhn-Tucker type necessary optimality conditions are a direct precipitation from Craven [5].

Definition 3.2. (Slater-type cone constraint qualification). The problem (NVOP) is said to satisfy Slater-type cone constraint qualification at \bar{x} if, for all $B \in \partial g(\bar{x})$, there exists a vector $\Omega \in \mathbf{R}^n$ such that $B\Omega \in -\text{int } Q$.

Theorem 3.3. If a vector $\bar{x} \in S_0$ is a weak minimum for (NVOP) with $S = \mathbf{R}^n$ at which Slater-type cone constraint qualification holds, then there exist Lagrange multipliers $\bar{\lambda} \in K^* \setminus \{0\}$ and $\bar{\mu} \in Q^*$, such that

$$0 \in \partial(\bar{\lambda}^t f + \bar{\mu}^t g)(\bar{x})$$

$$\bar{\mu}^t g(\bar{x}) = 0.$$

Note that, for $\bar{\lambda} = (\bar{\lambda}_1, \dots, \bar{\lambda}_m)^t \in \mathbf{R}^m$ and $\bar{\mu} = (\bar{\mu}_1, \dots, \bar{\mu}_p)^t \in \mathbf{R}^p$,

$$\partial(\bar{\lambda}^t f + \bar{\mu}^t g)(\bar{x}) \subseteq (\partial f(\bar{x})^t \bar{\lambda} + \partial g(\bar{x})^t \bar{\mu}).$$

Now we give the generalized form of nonsmooth KKT sufficient optimality conditions for (NVOP).

Theorem 3.4. Let f be K -generalized (Φ, ρ) -convex and g be Q -generalized (Φ, σ) -convex at $\bar{x} \in S_0$ on S_0 . If there exist $\bar{\lambda} \in K^* \setminus \{0\}$ and $\bar{\mu} \in Q^*$, such that

$$0 \in (\partial f(\bar{x})^t \bar{\lambda} + \partial g(\bar{x})^t \bar{\mu}), \quad (1)$$

$$\bar{\mu}^t g(\bar{x}) = 0, \quad (2)$$

$$\sum_{i=1}^m \bar{\lambda}_i + \sum_{j=1}^p \bar{\mu}_j > 0, \quad (3)$$

$$\bar{\lambda}^t \rho + \bar{\mu}^t \sigma \geq 0, \quad (4)$$

then \bar{x} is a weak minimum for (NVOP).

Proof: Suppose to the contrary that \bar{x} is not a weak minimum for (NVOP). Then there exists $\hat{x} \in S_0$ such that

$$f(\hat{x}) - f(\bar{x}) \in -\text{int } K. \quad (5)$$

By virtue of (1), there exist

$$\bar{A} = (\bar{A}_1, \dots, \bar{A}_m)^t \in \partial f(\bar{x})$$

and $\bar{B} = (\bar{B}_1, \dots, \bar{B}_p)^t \in \partial g(\bar{x})$

such that,

$$\bar{A}^t \bar{\lambda} + \bar{B}^t \bar{\mu} = 0. \quad (6)$$

Since f is K -generalized (Φ, ρ) -convex at \bar{x} on S_0 , we have

$$f(\hat{x}) - f(\bar{x}) - \Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) \in K. \quad (7)$$

Adding (5) and (7) we get,

$$\Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) \in -\text{int } K. \quad (8)$$

Since $\bar{\lambda} \in K^* \setminus \{0\}$, we have

$$\bar{\lambda}^t \Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) < 0. \quad (9)$$

Also, since g is Q -generalized (Φ, σ) -convex at \bar{x} on S_0 and $\bar{\mu} \in Q^*$, therefore

$$\bar{\mu}^t \{g(\hat{x}) - g(\bar{x}) - \Phi(\hat{x}, \bar{x}; (\bar{B}, \sigma))\} \geq 0.$$

However, $\hat{x} \in S_0$, $\bar{\mu} \in Q^*$ and (2) together imply

$$\bar{\mu}^t \Phi(\hat{x}, \bar{x}; (\bar{B}, \sigma)) \leq 0. \quad (10)$$

From (9) and (10), we have

$$\bar{\lambda}^t \Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) + \bar{\mu}^t \Phi(\hat{x}, \bar{x}; (\bar{B}, \sigma)) < 0. \quad (11)$$

Define $\tau = \frac{1}{\sum_{i=1}^m \bar{\lambda}_i + \sum_{j=1}^p \bar{\mu}_j}$,

$$\bar{\xi}_i = \tau \bar{\lambda}_i, \quad i = 1, 2, \dots, m,$$

$$\bar{\zeta}_j = \tau \bar{\mu}_j, \quad j = 1, 2, \dots, p.$$

Let $\bar{\xi} = (\bar{\xi}_1, \dots, \bar{\xi}_m)^t$ and $\bar{\zeta} = (\bar{\zeta}_1, \dots, \bar{\zeta}_p)^t$.

(3), (4) and (6) respectively imply $\tau > 0$, $\bar{\xi}^t \rho + \bar{\zeta}^t \sigma \geq 0$ and $\bar{\xi}^t \bar{A} + \bar{\zeta}^t \bar{B} = 0$.

Also, by definition $\sum_{i=1}^m \bar{\xi}_i + \sum_{j=1}^p \bar{\zeta}_j = 1$.

Thus, using the properties of Φ , we have

$$\begin{aligned}
& 0 \leq \varphi(\hat{x}, \bar{x}; (\bar{\xi}^t \bar{A} + \bar{\zeta}^t \bar{B}, \bar{\xi}^t \rho + \bar{\zeta}^t \sigma)) \\
& = \varphi(\hat{x}, \bar{x}; (\sum_{i=1}^m \bar{\xi}_i \bar{A}_i + \sum_{j=1}^p \bar{\zeta}_j \bar{B}_j, \sum_{i=1}^m \bar{\xi}_i \rho_i + \sum_{j=1}^p \bar{\zeta}_j \sigma_j)) \\
& \leq \sum_{i=1}^m \bar{\xi}_i \varphi(\hat{x}, \bar{x}; (\bar{A}_i, \rho_i)) + \sum_{j=1}^p \bar{\zeta}_j \varphi(\hat{x}, \bar{x}; (\bar{B}_j, \sigma_j)) \\
& = \tau(\bar{\lambda}^t \Phi(\hat{x}, \bar{x}; (\bar{A}, \rho))) + \bar{\mu}^t \Phi(\hat{x}, \bar{x}; (\bar{B}, \sigma)) < 0 \\
& \quad \text{(by (11)),}
\end{aligned}$$

which is a contradiction.

Hence, \bar{x} is a weak minimum for (NVOP).

Theorem 3.5. Let f be K -generalized (Φ, ρ) -pseudoconvex and g be Q -generalized (Φ, σ) -quasiconvex at $\bar{x} \in S_0$ on S_0 and suppose there exist $\bar{\lambda} \in K^* \setminus \{0\}$ and $\bar{\mu} \in Q^*$ such that (1), (2), (3) and (4) hold, then \bar{x} is a weak minimum for (NVOP).

Proof. Let, if possible, \bar{x} be not a weak minimum for (NVOP). Then there exists $\hat{x} \in S_0$ such that (5) holds.

In view of (1) there exist $\bar{A} \in \partial f(\bar{x})$ and $\bar{B} \in \partial g(\bar{x})$ such that (6) is satisfied.

Since f is K -generalized (Φ, ρ) -pseudoconvex at \bar{x} on S_0 , therefore from (5), we have

$$-\Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) \in \text{int } K.$$

Now $\bar{\lambda} \in K^* \setminus \{0\}$ gives $\bar{\lambda}^t \Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) < 0$.

As $\hat{x} \in S_0$ and $\bar{\mu} \in Q^*$, we have $\bar{\mu}^t g(\hat{x}) \leq 0$. On using (2), we get

$$\bar{\mu}^t \{g(\hat{x}) - g(\bar{x})\} \leq 0. \quad (12)$$

If $\bar{\mu} \neq 0$, then (12) implies $g(\hat{x}) - g(\bar{x}) \notin \text{int } Q$.

Since g is Q -generalized (Φ, σ) -quasiconvex at \bar{x} on S_0 , therefore

$$-\Phi(\hat{x}, \bar{x}; (\bar{B}, \sigma)) \in Q,$$

so that, $\bar{\mu}^t \Phi(\hat{x}, \bar{x}; (\bar{B}, \sigma)) \leq 0$. (13)

If $\bar{\mu} = 0$, then also (13) holds.

Now proceeding as in the last part of Theorem 3.4, we get a contradiction. Hence \bar{x} is a weak minimum for (NVOP).

Theorem 3.6. Let f be K -generalized (Φ, ρ) -convex and g be Q -generalized (Φ, σ) -convex at

$\bar{x} \in S_0$ on S_0 . Suppose there exist $\bar{\lambda} \in K^{s*}$ and $\bar{\mu} \in Q^*$ such that (1), (2), (3) and (4) hold, then \bar{x} is a minimum for (NVOP).

Proof. Let if possible \bar{x} be not a minimum for (NVOP), then there exists $\hat{x} \in S_0$ such that

$$f(\bar{x}) - f(\hat{x}) \in K \setminus \{0\}. \quad (14)$$

As (1) holds, there exist $\bar{A} \in \partial f(\bar{x})$ and $\bar{B} \in \partial g(\bar{x})$ such that (6) holds.

Since f is K -generalized (Φ, ρ) -convex at \bar{x} on S_0 , therefore proceeding on the similar lines as in proof of Theorem 3.4 and using (14) we have

$$-\Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) \in K \setminus \{0\}.$$

As $\bar{\lambda} \in K^{s*}$, we have $\bar{\lambda}^t \Phi(\hat{x}, \bar{x}; (\bar{A}, \rho)) < 0$.

This leads to a contradiction as in Theorem 3.4. Hence \bar{x} is a minimum for (NVOP).

4. Duality

We associate with the primal problem (NVOP), the following Wolfe-type dual problem (NWOD):

$$\text{(NWOD)} K\text{-maximize } f(y) + \mu^t g(y)l$$

$$\text{subject to } 0 \in (\partial f(y)^t \lambda + \partial g(y)^t \mu), \quad (15)$$

$$y \in S, l \in \text{int } K, \lambda \in K^* \setminus \{0\}, \mu \in Q^* \text{ and } \lambda^t l = 1.$$

We now establish duality results between (NVOP) and (NWOD).

Let W denote the set of feasible solutions of (NWOD) and Y_w be the subset of S given by $Y_w = \{y \in S : (y, \lambda, \mu) \in W\}$.

Theorem 4.1.(Weak Duality). Let x be feasible for (NVOP) and (y, λ, μ) be feasible for (NWOD). If f is K -generalized (Φ, ρ) -convex at y on $S_0 \cup Y_w$, g is Q -generalized (Φ, σ) -convex at

$$y \text{ on } S_0 \cup Y_w, \quad \sum_{i=1}^m \lambda_i + \sum_{j=1}^p \mu_j > 0 \quad \text{and}$$

$$\lambda^t \rho + \mu^t \sigma \geq 0, \text{ then}$$

$$f(y) + \mu^t g(y)l - f(x) \notin \text{int } K. \quad (16)$$

Proof. Let if possible, $f(y) + \mu^t g(y)l - f(x) \in \text{int } K$. (17)

Since (y, λ, μ) is feasible for (NWOD), therefore by (15), there exist

$\bar{A} \in \partial f(y)$ and $\bar{B} \in \partial g(y)$ such that

$$\bar{A}'\lambda + \bar{B}'\mu = 0. \quad (18)$$

Since f is K -generalized (Φ, ρ) -convex at y on $S_0 \cup Y_w$, therefore

$$f(x) - f(y) - \Phi(x, y; (\bar{A}, \rho)) \in K. \quad (19)$$

Adding (17) and (19), we get

$$\mu' g(y)l - \Phi(x, y; (\bar{A}, \rho)) \in \text{int } K.$$

As $\lambda \in K^* \setminus \{0\}$ and $\lambda'l = 1$, we have

$$\mu' g(y) - \lambda' \Phi(x, y; (\bar{A}, \rho)) > 0. \quad (20)$$

Again, since $x \in S_0$, g is Q -generalized (Φ, σ) -convex at y on $S_0 \cup Y_w$ and $\mu \in Q^*$, therefore

$$\mu' [g(x) - g(y) - \Phi(x, y; (\bar{B}, \sigma))] \geq 0. \quad (21)$$

From (20) and (21), we have $\lambda' \Phi(x, y; (\bar{A}, \rho)) + \mu' \Phi(x, y; (\bar{B}, \sigma)) < \mu' g(x)$.

Since x is feasible for (NVOP) and $\mu \in Q^*$, $\mu' g(x) \leq 0$, so that we have

$$\lambda' \Phi(x, y; (\bar{A}, \rho)) + \mu' \Phi(x, y; (\bar{B}, \sigma)) < 0.$$

Now proceeding as in proof of Theorem 3.4, we obtain a contradiction. Hence (16) holds.

This weak duality result allows us to obtain strong duality result as follows.

Theorem 4.2. (Strong Duality). Let \bar{x} be a weak minimum for (NVOP) at which Slater-type cone constraint qualification is satisfied. Then there exist $\bar{\lambda} \in K^* \setminus \{0\}$ and $\bar{\mu} \in Q^*$ such that $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is feasible for (NWOD). Moreover, if the conditions of Theorem 4.1, are satisfied for each feasible solution of (NWOD), then \bar{x} is a weak maximum for (NWOD).

Proof. Since \bar{x} is a weak minimum of (NVOP), therefore by Theorem 3.3, there exist $\bar{\lambda} \in K^* \setminus \{0\}$, $\bar{\mu} \in Q^*$ such that (1) and (2) hold.

Thus $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is feasible for (NWOD). Now assume on the contrary that $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is not a weak maximum for (NWOD), then there exists a feasible solution (y, λ, μ) for (NWOD) such that

$$\{f(y) + \mu' g(y)l\} - \{f(\bar{x}) + \bar{\mu}' g(\bar{x})l\} \in \text{int } K,$$

which on using (2) gives

$$f(y) + \mu' g(y)l - f(\bar{x}) \in \text{int } K.$$

This contradicts Weak Duality Theorem 4.1. Hence $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is a weak maximum for (NWOD).

Now we consider the following Mond-Weir type dual (NMOD) related to problem (NVOP):

(NMOD) K -maximize $f(y)$

$$\text{subject to } 0 \in \partial f(y)' \lambda + \partial g(y)' \mu \quad (22)$$

$$\mu' g(y) \geq 0, \quad (23)$$

$$y \in S, \lambda \in K^* \setminus \{0\} \text{ and } \mu \in Q^*.$$

Let M denote the set of feasible solutions of (NMOD) and Y_M be the subset of S defined by $Y_M = \{y \in S : (y, \lambda, \mu) \in M\}$.

Theorem 4.3. (Weak Duality). Let x be feasible for (NVOP) and (y, λ, μ) be feasible for (NMOD). Suppose f is K -generalized (Φ, ρ) -pseudoconvex and g is Q -generalized (Φ, σ) -quasiconvex at y on $S_0 \cup Y_M$ such that

$$\sum_{i=1}^m \lambda_i + \sum_{j=1}^p \mu_j > 0 \text{ and } \lambda' \rho + \mu' \sigma \geq 0, \text{ then}$$

$$f(y) - f(x) \notin \text{int } K. \quad (24)$$

Proof. Assume on the contrary,

$$f(y) - f(x) \in \text{int } K. \quad (25)$$

Since (y, λ, μ) is feasible for (NMOD), there exist $\bar{A} \in \partial f(y)$ and $\bar{B} \in \partial g(y)$ such that (18) holds.

As f is K -generalized (Φ, ρ) -pseudoconvex at y on $S_0 \cup Y_M$, therefore from (25), we have

$$-\Phi(x, y; (\bar{A}, \rho)) \in \text{int } K.$$

Since $\lambda \in K^* \setminus \{0\}$, we get $\lambda' \Phi(x, y; (\bar{A}, \rho)) < 0$.

Also, $x \in S_0$ and $\mu \in Q^*$ so that $\mu' g(x) \leq 0$. This together with (23) gives $\mu' \{g(x) - g(y)\} \leq 0$.

Now proceeding on similar lines as in proof of Theorem 3.5 we get a contradiction. Hence (24) holds.

Theorem 4.4. (Strong Duality). Let \bar{x} be a weak minimum of (NVOP) at which Slater-type cone constraint qualification is satisfied. Then there exist $\bar{\lambda} \in K^* \setminus \{0\}$ and $\bar{\mu} \in Q^*$ such that

$(\bar{x}, \bar{\lambda}, \bar{\mu})$ is feasible for (NMOD). Moreover, if the conditions of Weak Duality Theorem 4.3 are satisfied for each feasible solution (y, λ, μ) of (NMOD), then $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is a weak maximum of (NMOD).

Proof. The proof is similar to that of Theorem 4.2 except that we invoke Theorem 4.3 instead of Theorem 4.1.

Acknowledgments

The authors would like to thank the reviewers for their valuable comments that helped to improve the manuscript.

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