OPTIMALITY AND DUALITY FOR GENERALIZED NONDIFFERENTIABLE FRACTIONAL PROGRAMMING WITH GENERALIZED INVEXITY †

MOON HEE KIM* AND GWI SOO KIM

ABSTRACT. Sufficient optimality conditions for a class of generalized non-differentiable fractional optimization programming problems are established. Moreover, we prove the weak and strong duality theorems under (V,ρ) -invexity assumption.

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1. Introduction

In this paper, we consider the following generalized nondifferentiable fractional optimization problem (GFP):

$$(\text{GFP}) \qquad \quad \text{Minimize} \qquad \max \left\{ \frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)} \mid i = 1, \cdots, p \right\}$$
 subject to
$$\quad h_j(x) \leq 0, \quad j = 1, \cdots, m,$$

where $f:=(f_1,\dots,f_p):\mathbb{R}^n\to\mathbb{R}^p,\ g:=(g_1,\dots,g_p):\mathbb{R}^n\to\mathbb{R}^p$ and $h:=(h_1,\dots,h_m):\mathbb{R}^n\to\mathbb{R}^m$ are continuously differentiable. We assume that $g_i(x)-s(x|D_i)>0,\ i=1,\dots,p.$ For each $i=1,\dots,p,\ C_i$ and D_i are compact convex set of \mathbb{R}^n and we define a support function with respect to C_i as follows:

$$s(x|C_i) := \max\{\langle x, y_i \rangle \mid y_i \in C_i\}.$$

Further let, $J(x) = \{j : h_j(x) = 0\}$, for any $x \in \mathbb{R}^n$ and let

$$k_i(x) = s(x|C_i), \quad i = 1, \dots, p.$$

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Then, k_i is a convex function and we can prove that

$$\partial k_i(x) = \{ w_i \in C_i \mid \langle w_i, x \rangle = s(x|C_i) \},\$$

where ∂k_i is the subdifferential of k_i .

Many authors have introduced various concepts of generalized convexity and have obtained optimality and duality results for a fractional programming problem ([2]–[9], [11]).

Recently, Kim and Kim [4] consider the following generalized nondifferentiable fractional optimization problem.

where $f:=(f_1,\dots,f_p):\mathbb{R}^n\to\mathbb{R}^p,\ g:=(g_1,\dots,g_p):\mathbb{R}^n\to\mathbb{R}^p$ and $h:=(h_1,\dots,h_m):\mathbb{R}^n\to\mathbb{R}^m$ are continuously differentiable. We assume that $g_i(x)>0,\ i=1,\dots,p.$ For each $i=1,\dots,p,\ C_i$ are compact convex set of \mathbb{R}^n .

In this paper, we apply the approach of Kim and Kim [4] to the generalized nondifferentiable fractional optimization problem (GFP), we establish the necessary and sufficient optimality conditions for a class of generalized nondifferentiable fractional optimization problem (GFP). Moreover, we prove the weak and strong duality theorems under (V, ρ) -invexity assumptions.

We introduce the following definition due to Kuk et al. [5].

Definition 1. A vector function $f: \mathbb{R}^n \to \mathbb{R}^p$ is said to be (V, ρ) -invex at $u \in \mathbb{R}^n$ with respect to the functions η and $\theta_i: \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n$ if there exists $\alpha_i: \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}_+ \setminus \{0\}$ and $\rho_i \in \mathbb{R}, i = 1, \dots, p$ such that for any $x \in \mathbb{R}^n$ and for all $i = 1, \dots, p$,

$$\alpha_i(x,u)[f_i(x) - f_i(u)] \ge \nabla f_i(u)\eta(x,u) + \rho_i \|\theta_i(x,u)\|^2.$$

Definition 2. A vector function $f: \mathbb{R}^n \to \mathbb{R}^p$ is said to be η -invex at $u \in \mathbb{R}^n$ such that for any $x \in \mathbb{R}^n$ and for all $i = 1, \dots, p$,

$$f_i(x) - f_i(u) \ge \nabla f_i(u) \eta(x, u).$$

We give the following theorem due to Kim et al. [2].

Theorem 1. Assume that f and g are vector-valued differentiable functions defined on X_0 and $f(x) + \langle w, x \rangle \geq 0$, $g(x) - \langle \widetilde{w}, x \rangle > 0$ for all $x \in X_0$. If

 $f(\cdot) + \langle w, \cdot \rangle$ and $-g(\cdot) + \langle \widetilde{w}, \cdot \rangle$ are (V, ρ) -invex at $x_0 \in X_0$, then $\frac{f(\cdot) + \langle w, \cdot \rangle}{g(\cdot) - \langle \widetilde{w}, \cdot \rangle}$ is (V, ρ) -invex at x_0 , where

$$\bar{\alpha}_i(x,x_0) = \frac{g_i(x) - \langle \widetilde{w}_i, x \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \alpha_i(x,x_0), \quad \bar{\theta}_i(x,x_0) = \left(\frac{1}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle}\right)^{\frac{1}{2}} \theta_i(x,x_0),$$

that is, for all i,

$$\begin{aligned} &\alpha_{i}(x,x_{0}) \left[\frac{f_{i}(x) + \langle w_{i}, x \rangle}{g_{i}(x) - \langle \widetilde{w}_{i}, x \rangle} - \frac{f_{i}(x_{0}) + \langle w_{i}, x_{0} \rangle}{g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle} \right] \\ &\geq \frac{g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle}{g_{i}(x) - \langle \widetilde{w}_{i}, x \rangle} \left[\nabla \left(\frac{f_{i}(x_{0}) + \langle w_{i}, x_{0} \rangle}{g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle} \right) \eta_{i}(x, x_{0}) \right. \\ &\left. + \rho_{i} \| \left(\frac{1}{g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle} \right)^{\frac{1}{2}} \theta_{i}(x, x_{0}) \|^{2} \right]. \end{aligned}$$

Proof. Let $k_i(x) = s(x|C_i)$ and $\widetilde{k}_i(x) = s(x|D_i)$, $i = 1, \ldots, p$. Choose $w_i \in \partial k_i(x_0)$ and $\widetilde{w}_i \in \partial \widetilde{k}_i(x_0)$. Let $x, x_0 \in X_0$. By the (V, ρ) -invexity of $f(\cdot) + \langle w, \cdot \rangle$ and $-g + \langle \widetilde{w}, \cdot \rangle$,

$$\begin{split} &\alpha_i(x,x_0) \ \Big[\ \frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} - \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \ \Big] \\ &= \alpha_i(x,x_0) \Big[\frac{f_i(x) + \langle w_i, x \rangle - f_i(x_0) - \langle w_i, x_0 \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} \\ &- (f_i(x_0) + \langle w_i, x_0 \rangle) \frac{g_i(x) - \langle \widetilde{w}_i, x \rangle - g_i(x_0) + \langle \widetilde{w}_i, x_0 \rangle}{(g_i(x) - \langle \widetilde{w}_i, x \rangle)(g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle)} \Big] \\ &\geq \frac{1}{g_i(x) - \langle \widetilde{w}_i, x \rangle} \Big[(\nabla f_i(x_0) + w_i) \eta_i(x, x_0) + \rho_i \|\theta_i(x, x_0)\|^2 \Big] \\ &+ \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{(g_i(x) - \langle \widetilde{w}_i, x \rangle)(g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle)} \Big[(-\nabla g_i(x_0) + \widetilde{w}_i) \eta_i(x, x_0) + \rho_i \|\theta_i(x, x_0)\|^2 \Big]. \end{split}$$

Since $g(x) - \langle \widetilde{w}, x \rangle > 0$ for all $x \in X_0$, we see that

$$\begin{split} &\alpha_i(x,x_0) \Big[\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} - \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \Big] \\ &\geq \frac{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} \Big[\frac{\nabla f_i(x_0) + w_i}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \eta_i(x, x_0) + \rho_i \| \Big(\frac{1}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \Big)^{\frac{1}{2}} \theta_i(x, x_0) \|^2 \\ &\quad - \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{(g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle)^2} (\nabla g_i(x_0) - \widetilde{w}_i) \eta_i(x, x_0) + \rho_i \| \Big(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{(g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle)^2} \Big)^{\frac{1}{2}} \theta_i(x, x_0) \|^2 \Big]. \end{split}$$

Thus, we have

$$\begin{split} &\alpha_{i}(x,x_{0}) \Big[\frac{f_{i}(x) + \langle w_{i},x \rangle}{g_{i}(x) - \langle \widetilde{w}_{i},x \rangle} - \frac{f_{i}(x_{0}) + \langle w_{i},x_{0} \rangle}{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle} \Big] \\ &\geq \frac{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle}{g_{i}(x) - \langle \widetilde{w}_{i},x \rangle} \\ & \Big[\frac{(\nabla f_{i}(x_{0}) + w_{i})(g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle) - (f_{i}(x_{0}) + \langle \widetilde{w}_{i},x_{0} \rangle)(\nabla g_{i}(x_{0}) - \widetilde{w}_{i})}{(g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle)^{2}} \eta_{i}(x,x_{0}) \\ & + \rho_{i} \| \Big(\frac{1}{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle} \Big)^{\frac{1}{2}} \theta_{i}(x,x_{0}) \|^{2} + \rho_{i} \| \Big(\frac{f_{i}(x_{0}) + \langle w_{i},x_{0} \rangle}{(g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle)^{2}} \Big)^{\frac{1}{2}} \theta_{i}(x,x_{0}) \|^{2} \Big] \\ & = \frac{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle}{g_{i}(x) - \langle \widetilde{w}_{i},x_{0} \rangle} \Big[\nabla \Big(\frac{f_{i}(x_{0}) + \langle w_{i},x_{0} \rangle}{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle} \Big) \eta_{i}(x,x_{0}) \\ & + \rho_{i} \| \Big(\frac{1}{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle} \Big)^{\frac{1}{2}} \Big(1 + \Big(\frac{f_{i}(x_{0}) + \langle w_{i},x_{0} \rangle}{g_{i}(x_{0}) - \langle \widetilde{w}_{i},x_{0} \rangle} \Big)^{\frac{1}{2}} \Big) \theta_{i}(x,x_{0}) \|^{2} \Big]. \end{split}$$

Considering that

$$1 + \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle}\right)^{\frac{1}{2}} \ge 1, \ i = 1, 2, \dots, p,$$

we have for all i,

$$\begin{aligned} &\alpha_{i}(x,x_{0})\Big[\frac{f_{i}(x)+\langle w_{i},x\rangle}{g_{i}(x)-\langle\widetilde{w}_{i},x\rangle}-\frac{f_{i}(x_{0})+\langle w_{i},x_{0}\rangle}{g_{i}(x_{0})-\langle\widetilde{w}_{i},x_{0}\rangle}\Big]\\ &\geq \frac{g_{i}(x_{0})-\langle\widetilde{w}_{i},x_{0}\rangle}{g_{i}(x)-\langle\widetilde{w}_{i},x\rangle}\Big[\nabla\Big(\frac{f_{i}(x_{0})+\langle w_{i},x_{0}\rangle}{g_{i}(x_{0})-\langle\widetilde{w}_{i},x_{0}\rangle}\Big)\eta_{i}(x,x_{0})+\rho_{i}\|\Big(\frac{1}{g_{i}(x_{0})-\langle\widetilde{w}_{i},x_{0}\rangle}\Big)^{\frac{1}{2}}\theta_{i}(x,x_{0})\|^{2}\Big]. \end{aligned}$$

Therefore, the function $\frac{f(x)+\langle w,x\rangle}{g(x)-\langle \widetilde{w},x\rangle}$ is (V,ρ) -invex, where

$$\bar{\alpha}_i(x, x_0) = \frac{g_i(x) - \langle \widetilde{w}_i, x \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \alpha_i(x, x_0),$$

$$\bar{\theta}_i(x, x_0) = \left(\frac{1}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle}\right)^{\frac{1}{2}} \theta_i(x, x_0).$$

2. Optimality Conditions

Now, we establish the Kuhn-Tucker necessary and sufficient conditions for a solution of (GFP).

Theorem 2. (Kuhn-Tucker Necessary Optimality Theorem) If x_0 is a solution of (GFP), and assume that $0 \notin co\{\nabla h_j(x_0) \mid j \in J(x_0)\}$, then there exist

$$\lambda_i \geq 0, \ i \in I(x_0) := \{i \mid \max\left\{\frac{f_i(x_0) + s(x_0|C_i)}{g_i(x_0) - s(x_0|D_i)} \mid i = 1, \cdots, p\right\}\}, \ \sum_{i \in I(x_0)} \lambda_i = 1, \ \mu_j \geq 0, \ j = 1, \cdots, m \ \text{and} \ w_i \in C_i, \ \widetilde{w}_i \in D_i, \ i \in I(x_0) \ \text{such that}$$

$$\sum_{i \in I(x_0)} \lambda_i \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(x_0) = 0,$$

$$\langle w_i, x_0 \rangle = s(x_0 | C_i), \ \langle \widetilde{w}_i, x_0 \rangle = s(x_0 | D_i),$$

$$\sum_{j=1}^m \mu_j h_j(x_0) = 0.$$

Proof. Let $\varphi_i(x) = \frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)}, i = 1, \dots, p$. Let x_0 be a solution of (GFP) and let $I(x_0) = \{i \mid \max\{\varphi_i(x_0) \mid i = 1, \dots, p\}\}$. Then by Proposition 2.3.12 in [1] and Corollary 5.1.8 in [10], there exists $\mu_j \geq 0, \ j = 1, \dots, m$,

$$0 \in \operatorname{co}\{\partial^{c}\varphi_{i}(x_{0}) \mid i \in I(x_{0})\} + \sum_{j=1}^{m} \mu_{j}\partial^{c}h_{j}(x_{0})$$

and $\mu_{j}h_{j}(x_{0}) = 0$.

Thus there exists $\lambda_i \geq 0$, $i \in I(x_0)$, $\sum_{i \in I(x_0)} \lambda_i = 1$ such that

$$0 \in \sum_{i \in I(x_0)} \lambda_i \partial^c \varphi_i(x_0) + \sum_{j=1}^m \mu_j \nabla h_j(x_0)$$
 and
$$\mu_j h_j(x_0) = 0.$$
 (2.1)

By Proposition 2.3.14 in [1],

$$\partial^{c} \varphi_{i}(x_{0}) = \frac{1}{(g_{i}(x_{0}) - s(x_{0}|D_{i}))^{2}} \Big((g_{i}(x_{0}) - s(x_{0}|D_{i}))(\nabla f_{i}(x_{0}) + \partial s(x_{0}|C_{i})) - (f_{i}(x_{0}) + s(x_{0}|C_{i}))(\nabla g_{i}(x_{0}) - \partial s(x_{0}|D_{i})) \Big).$$

Since

$$\partial^{c}\varphi_{i}(x_{0}) = \begin{cases} \frac{1}{(g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle)^{2}} \Big((g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle) (\nabla f_{i}(x_{0}) + w_{i}) \\ - (f_{i}(x_{0}) + \langle w_{i}, x_{0} \rangle) (\nabla g_{i}(x_{0}) - \widetilde{w}_{i}) \Big) | \ w_{i} \in C_{i}, \ \langle w_{i}, x_{0} \rangle = s(x_{0}|C_{i}), \\ \langle \widetilde{w}_{i}, x_{0} \rangle = s(x_{0}|D_{i}), \ i \in I(x_{0}) \} \end{cases}$$

$$= \begin{cases} \nabla \Big(\frac{f_{i}(x_{0}) + \langle w_{i}, x_{0} \rangle}{g_{i}(x_{0}) - \langle \widetilde{w}_{i}, x_{0} \rangle} \Big) | w_{i} \in C_{i}, \ \widetilde{w}_{i} \in D_{i}, \ \langle w_{i}, x_{0} \rangle = s(x_{0}|C_{i}), \\ \langle \widetilde{w}_{i}, x_{0} \rangle = s(x_{0}|D_{i}), \ i \in I(x_{0}) \} \end{cases}$$

and hence from (2.1), there exist $\lambda_i \geq 0$, $i \in I(x_0)$, $\sum_{i \in I(x_0)} \lambda_i = 1$, $\mu_j \geq 0$, $j = 1, \dots, m$ and $w_i \in C_i$, $i \in I(x_0)$ such that

$$\sum_{i \in I(x_0)} \lambda_i \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(x_0) = 0,$$

$$\langle w_i, x_0 \rangle = s(x_0 | C_i), \ \langle \widetilde{w}_i, x_0 \rangle = s(x_0 | D_i),$$

$$\sum_{j=1}^m \mu_j h_j(x_0) = 0.$$

Theorem 3. (Kuhn-Tucker Sufficient Optimality Theorem) Let x_0 be a feasible solution of (GFP). Suppose that there exist $\lambda_i \geq 0$, $i \in I(x_0)$, $\sum_{i \in I(x_0)} \lambda_i = 1, \ \mu_j \geq 0, \ j = 1, \cdots, m$ and $w_i \in C_i, \ \widetilde{w}_i \in D_i, \ i \in I(x_0)$ such that

$$\sum_{i \in I(x_0)} \lambda_i \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(x_0) = 0,$$

$$\langle w_i, x_0 \rangle = s(x_0 | C_i), \ \langle \widetilde{w}_i, x_0 \rangle = s(x_0 | D_i),$$

$$\sum_{j=1}^m \mu_j h_j(x_0) = 0.$$
(2.2)

If $f(\cdot)+\langle w,\cdot\rangle$ and $-g(\cdot)+\langle \widetilde{w},\cdot\rangle$ are (V,ρ) -invex at x_0 , and h is η -invex at x_0 with respect to the same η , and $\sum_{i\in I(x_0)}\lambda_i\rho_i\|\bar{\theta}_i(x,x_0)\|^2\geq 0$, then x_0 is a solution of (GFP).

Proof. Suppose that x_0 is not a solution of (GFP). Then there exist a feasible solution x of (GFP) such that

$$\max_{1 \leq i \leq p} \frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)} < \max_{1 \leq i \leq p} \frac{f_i(x_0) + s(x_0|C_i)}{g_i(x_0) - s(x_0|D_i)}.$$

Then

$$\frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)} < \frac{f_i(x_0) + s(x_0|C_i)}{g_i(x_0) - s(x_0|D_i)}, \text{ for all } i \in I(x_0).$$

Since $\langle w_i, x_0 \rangle = s(x_0|C_i)$, $w_i \in C_i$, and $\langle \widetilde{w}_i, x_0 \rangle = s(x_0|D_i)$, $\widetilde{w}_i \in D_i$, we have for all $i \in I(x_0)$,

$$\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} \leq \frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)} \\
< \frac{f_i(x_0) + s(x_0|C_i)}{g_i(x_0) - s(x_0|D_i)} \\
= \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle}$$

and hence $\bar{\alpha}_i(x, x_0) > 0$,

$$\bar{\alpha}_i(x, x_0) \left[\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} - \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \right] < 0.$$

By the (V, ρ) -invexity of $f(\cdot) + \langle w, \cdot \rangle$ and $-g(\cdot) + \langle \widetilde{w}, \cdot \rangle$ at x_0 , and by Theorem 1, we have

$$\nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle}\right) \eta(x, x_0) + \rho_i \|\bar{\theta}_i(x, x_0)\|^2 < 0.$$

Hence, we have

$$\sum_{i \in I(x_0)} \lambda_i \nabla \Big(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \Big) \eta(x, x_0) + \sum_{i \in I(x_0)} \lambda_i \rho_i \|\bar{\theta}_i(x, x_0)\|^2 < 0.$$

Since $\sum_{i \in I(x_0)} \lambda_i \rho_i \|\bar{\theta}_i(x, x_0)\|^2 \ge 0$,

$$\sum_{i \in I(x_0)} \lambda_i \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \widetilde{w}_i, x_0 \rangle} \right) \eta(x, x_0) < 0$$

and so, it follows from (2.2) that

$$\sum_{j=1}^{m} \mu_{j} \nabla h_{j}(x_{0}) \eta(x, x_{0}) > 0.$$

Then, by the η -invexity of h, we have

$$\sum_{j=1}^{m} \mu_j h_j(x) - \sum_{j=1}^{m} \mu_j h_j(x_0) > 0.$$

Since $\sum_{j=1}^{m} \mu_j h_j(x_0) = 0$, we have $\sum_{j=1}^{m} \mu_j h_j(x) > 0$, which is a contradiction since $\mu_j \geq 0$, $j = 1, \dots, m$ and x is a feasible solution of (GFP). Consequently, x_0 is a solution of (GFP).

3. Duality Theorems

Now, we propose the following Mond-Weir type dual problem (DGFP): (DGFP) $\,$

Maximize
$$\max \left\{ \frac{f_i(u) + s(u|C_i)}{g_i(u) - s(u|D_i)} \mid i = 1, \cdots, p \right\}$$
subject to
$$\sum_{i \in I(u)} \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \widetilde{w}_i, u \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(u) = 0, \tag{3.1}$$

$$w_i \in C_i, \ \widetilde{w}_i \in D_i, \ \langle w_i, u \rangle = s(u|C_i), \ \langle \widetilde{w}_i, u \rangle = s(u|D_i), \ i \in I(u)$$

$$\sum_{j=1}^m \mu_j h_j(u) = 0,$$

$$\lambda_i \geq 0, \ i \in I(u), \ \sum_{i \in I(u)} \lambda_i = 1, \ \mu_j \geq 0, \ j = 1, \cdots, m.$$

Now we show that the following weak duality theorem holds between (GFP) and (DGFP).

Theorem 4. (Weak Duality) Let x be a feasible for (GFP) and let (u, λ, μ, w) be feasible for (DGFP). Assume that $f(\cdot) + \langle w, \cdot \rangle$ and $-g(\cdot) + \langle \widetilde{w}, \cdot \rangle$ are (V, ρ) -invex at u, and let h is η -invex at u with respect to the same η , and $\sum_{i \in I(u)} \lambda_i \rho_i ||\bar{\theta}_i(x, u)||^2 \ge 0$. Then the following holds:

$$\max \left\{ \frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)} \mid i = 1, \cdots, p \right\} \ge \max \left\{ \frac{f_i(u) + s(u|C_i)}{g_i(u) - s(u|D_i)} \mid i = 1, \cdots, p \right\}.$$

Proof. Let x be any feasible for (GFP) and let (u, λ, μ, w) be any feasible for (DGFP). Then we have

$$\sum_{j=1}^{m} \mu_j h_j(x) \le 0 \le \sum_{j=1}^{m} \mu_j h_j(u).$$

By the η -invexity of $h_j(u)$, $j = 1, \dots, m$, we have

$$\sum_{j=1}^{m} \mu_j \nabla h_j(u) \eta(x, u) \le 0.$$

Using (3.1), we obtain

$$\sum_{i \in I(u)} \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \widetilde{w}_i, u \rangle} \right) \eta(x, u) \ge 0.$$
 (3.2)

Now suppose that

$$\max \left\{ \frac{f_i(x) + s(x|C_i)}{g_i(x) - s(x|D_i)} \mid i = 1, \dots, p \right\} < \max \left\{ \frac{f_i(u) + s(u|C_i)}{g_i(u) - s(u|D_i)} \mid i = 1, \dots, p \right\}.$$

Then

$$\frac{f_i(x)+s(x|C_i)}{g_i(x)-s(x|D_i)}<\frac{f_i(u)+s(u|C_i)}{g_i(u)-s(u|D_i)},\quad \text{for all } i\in I(u).$$

Since $\langle w_i, u \rangle = s(u|C_i)$ and $\langle \widetilde{w}_i, u \rangle = s(u|D_i)$, we have for all $i \in I(u)$,

$$\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \widetilde{w}_i, x \rangle} < \frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \widetilde{w}_i, u \rangle}.$$

By the (V, ρ) -invexity of $f(\cdot) + \langle w, \cdot \rangle$ and $-g(\cdot) + \langle \widetilde{w}, \cdot \rangle$ at x_0 , and by Theorem 1, we have,

$$0 > \bar{\alpha}_{i}(x,u) \left[\frac{f_{i}(x) + \langle w_{i}, x \rangle}{g_{i}(x) - \langle \widetilde{w}_{i}, x \rangle} - \frac{f_{i}(u) + \langle w_{i}, u \rangle}{g_{i}(u) - \langle \widetilde{w}_{i}, u \rangle} \right]$$

$$\geq \nabla \left(\frac{f_{i}(u) + \langle w_{i}, u \rangle}{g_{i}(u) - \langle \widetilde{w}_{i}, u \rangle} \right) \eta(x,u) + \rho_{i} \|\bar{\theta}_{i}(x,u)\|^{2}.$$

By using $\lambda_i \geq 0$, $i \in I(u)$, we have,

$$\sum_{i \in I(u)} \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \widetilde{w}_i, u \rangle} \right) \eta(x, u) + \sum_{i \in I(u)} \lambda_i \rho_i ||\bar{\theta}_i(x, u)||^2 < 0.$$

Since $\sum_{i \in I(u)} \lambda_i \rho_i \|\bar{\theta}_i(x, u)\|^2 \ge 0$, we have

$$\sum_{i \in I(u)} \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \widetilde{w}_i, u \rangle} \right) \eta(x, u) < 0,$$

which contradicts (3.2). Hence the result holds.

Now we give a strong duality theorem which holds between (GFP) and (DGFP).

Theorem 5. (Strong Duality) If \bar{x} be a solution of (GFP) and suppose that $0 \notin \operatorname{co}\{\nabla h_j(\bar{x}) \mid j \in J(\bar{x})\}$. Then there exist $\bar{\lambda} \in \mathbb{R}^p$, $\bar{\mu} \in \mathbb{R}^m$ and $\bar{w} \in C$ such that $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \overline{\widetilde{w}})$ is feasible for (DGFP). Moreover if the weak duality holds, then $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \overline{\widetilde{w}})$ is a solution of (DGFP).

Proof. By Theorem 2, there exist $\bar{\lambda} \in \mathbb{R}^p$, $\bar{\mu} \in \mathbb{R}^m$ and $\bar{w}_i \in C_i$, $\overline{\tilde{w}} \in D_i$, $i \in I(\bar{x})$, such that

$$\sum_{i \in I(\bar{x})} \bar{\lambda}_i \nabla \left(\frac{f_i(\bar{x}) + \langle \bar{w}_i, \bar{x} \rangle}{g_i(\bar{x}) - \langle \overline{\tilde{w}}_i, \bar{x} \rangle} \right) + \sum_{j=1}^m \bar{\mu}_j \nabla h_j(\bar{x}) = 0,$$

$$\langle \bar{w}_i, \bar{x} \rangle = s(\bar{x}|C_i), \ \langle \overline{\tilde{w}}_i, u \rangle = s(\bar{x}|D_i),$$

$$\sum_{j=1}^m \mu_j h_j(\bar{x}) = 0,$$

$$\lambda_i \ge 0, \ i \in I(\bar{x}), \ \sum_{i \in I(\bar{x})} \lambda_i = 1.$$

Thus $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \overline{\tilde{w}})$ is a feasible for (DGFP). On the other hand, by weak duality (Theorem 4),

$$\max\left\{\frac{f_i(\bar{x})+s(\bar{x}|C_i)}{g_i(\bar{x})-s(\bar{x}|D_i)}\mid i=1,\cdots,p\right\}\geq \max\left\{\frac{f_i(u)+s(u|C_i)}{g_i(u)-s(u|D_i)}\mid i=1,\cdots,p\right\}$$

for any (DGFP) feasible solution $(u, \lambda, \mu, w, \widetilde{w})$. Hence $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \widetilde{w})$ is a solution of (DGFP).

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Moon Hee Kim received her Ph. D at Pukyong National University under the direction of Professor Gue Myung Lee. Since 2006 she has been at the Tongmyong University. Her research interests focus on vector optimization problem and variational inequality.

Department of Multimedia Engineering, Tongmyong University, Pusan 608-711, Korea. e-mail: mooni@tu.ac.kr

Gwi Soo Kim received her Ph. D at Pukyong National University under the direction of Professor Gue Myung Lee. Since 2005 she has been at the Pukyong National University. Her research interests focus on vector optimization problem.

Department of Applied Mathematics, Pukyong National University, Pusan 608-737, Korea. e-mail: gwisoo1103@hanmail.net