

DUALITY FOR NONDIFFERENTIABLE MINIMAX MULTIOBJECTIVE FRACTIONAL OPTIMIZATION PROBLEMS WITH GENERALIZED INVEXITY

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Abstract: we introduce Kurush-Kuhn-Tucker sufficient optimality Mond-Weir type weak and strong duality theorems for a non-differentiable minimax fractional programming optimization problem in which numerator and denominator of multi objective each term consists of support function, under the assumptions of (V,σ,ρ) type-I invex functions.

Keywords: sufficient optimality conditions, duality theorems, generalized invexity, minimax fractional programming problems.

Introduction: There are several chapters devoted to this topic by Mishra and Giorgio [6], Clarke [2] and Craven [3]. In the recent past, KUK et al. [5] have introduced the concept of (V,ρ) - Convexity, which is generalization of the V -convexity for vector valued functions and derived the generalized Karush - Kuhn - Tucker optimality conditions as well as weak and strong duality for non smooth multi objective fractional programs. Later, Kim et al. [4] extended their result in presence of support functions. Very recently, Kim et al [4] have introduced the assumption of (V,ρ) - convexity for (F.P) the following generalized non differentiable fractional programming problem (GFP);

$$\text{Minimize} \max \left\{ \frac{f_i(x) + s(x/C_i)}{g_i(x) - s(x/D_i)} / i = 1, \dots, p \right\}$$

Subject to $h_j(x) \leq 0, j = 1, \dots, m$

Where

$$f := (f_1, \dots, f_p) : R^n \rightarrow R^p, g := (g_1, \dots, g_p) : R^n \rightarrow R^p$$

and

$$h := (h_1, \dots, h_m) : R^n \rightarrow R^m$$

are continuously differentiable and for each $i = 1, \dots, P$, C_i and D_i are compact convex sets of R^n

In this chapter, we introduce (V, P, σ) - convex function to derive the Kurush - Kuhn - Tucker Sufficient optimality and Mond - weir type weak and strong duality theorems for a generalized non differentiable minimax multi objective fractional optimization problem (GEP), in which numerator and denominator of each term consists of support function, and a constraint set defined by differentiable functions.

2 Preliminaries and definitions:-

In this chapter, we consider the following non differentiable multi objective fractional

programming problem.

(GFP)Minimize

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

Subject to : $h_j(x) \leq 0, j = 1, \dots, m$

Where

$$f := (f_1, \dots, f_p) : R^n \rightarrow R^p, g := (g_1, \dots, g_p) : R^n \rightarrow R^p$$

and

$$h := (h_1, \dots, h_m) : R^n \rightarrow R^m$$

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 sets of R^n and define the support functions with respect to C_i and D_i as follows.

$$s(x/C_i) = \max \{ \langle x, y_i \rangle / y_i \in C_i \}$$

And

$$s(x/D_i) = \max \{ \langle x, y_i \rangle / y_i \in D_i \}$$

Further denote $I(x) = \{ j / h_j(x) = 0 \}$ for any $x \in R^n$.

Let $k_i(x) = s(x/C_i)$ and $\tilde{k}_i(x) = s(x/D_i)$, $i = 1, \dots, P$.

Hence $k_i(x)$ and $\tilde{k}_i(x)$ are convex functions.

Choose $w_i \in dk_i(x)$ and $\tilde{w}_i \in d\tilde{k}_i(x)$ such that

$$dk_i(x) = \{ w_i \in C_i / \langle w_i, x \rangle = s(x/C_i) \}$$

And $d\tilde{k}_i(x) = \{ \tilde{w}_i \in D_i / \langle \tilde{w}_i, x \rangle = s(x/D_i) \}$

Where dk_i and $d\tilde{k}_i$ are the sub differential of k_i and \tilde{k}_i respectively. Further

$$\text{Let } S = \{ x \in R^n / h_j(x) \leq 0, j = 1, \dots, m \}$$

2.1 Definition:- A vector valued function $f : R^n \rightarrow R^p$ is said to be convex at $u \in R^n$ if for any $x \in R^n$ and for all $i = 1, \dots, p$ one has

$$f_i(x) - f_i(u) \geq \nabla f_i(u)(x-u)^t$$

2.2:- Definition:- A vector valued function $f : R^n \rightarrow R^p$ is said to be (V, ρ) -Convex at $u \in R^n$ with respect to the function $\alpha_i : R^n \times R^n \rightarrow R_+ / \{0\}$ and $\rho_i \in R, i = 1, \dots, p$, such that for any $x \in R^n$ and for all $i = 1, \dots, p$ it holds.

$$\alpha_i(x, u) [f_i(x) - f_i(u)] \geq \nabla f_i(u)(x-u)^t + \rho_i \|\theta_i(x, u)\|^2$$

The following Theorem from [] will be needed in the sequel.

2.3 Definition:-

Let $\left(\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} \right) = \theta_i(x), i = 1, \dots, p$

$$\langle w_i, x \rangle = s(x/C_i), \langle \tilde{w}_i, x \rangle = s(x/D_i)$$

The pair (ϕ_i, h_j) is called (V, ρ_i, σ_j) - convex at $u \in R^n$,

If there exist $\alpha_i : R^n \times R^n \rightarrow R_+ / \{0\}$

$$\bar{\alpha}_i(x, u) = \frac{g_i(x) + \langle \tilde{w}_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} \alpha_i(x, u) > 0$$

$$\bar{\theta}_i(x, u) = \left(\frac{1}{g_i(u) + \langle \tilde{w}_i, u \rangle} \right)^{\frac{1}{2}} \theta_i(x, u)$$

$$\beta_i : R^n \times R^n \rightarrow R_+ / \{0\},$$

$$\rho_i \in R, i = 1, \dots, P; \sigma_j \in R, j = 1, \dots, m$$

Such that

$$\theta_i(x) - \theta_i(u) \geq \bar{\alpha}_i(x, u) \nabla \theta_i(u)(x-u)^t + \rho_i \|\bar{\theta}_i(x, u)\|^2$$

and

$$-h_j(u) \geq \beta_j(x, u) \nabla h_j(u)(x-u)^t + \sigma_j \|\bar{\theta}_i(x, u)\|^2$$

3 Optimality Conditions:-

The following Kuhn -Tucker necessary optimality conditions for (GFP) from [] will be needed in the sequel.

3.1 Theorem : (Kuhn - Tucker necessary optimality condition) if x_0 is a solution of the problem (GFP) and under the assumption that one has $0 \notin C_0 \{ \nabla h_j(x_0) / j = 1, \dots, m \}$ then there exist $\lambda_i \geq 0$.

$$i \in I(x_0) := \left\{ i / \max_j \frac{f_j(x_0) + s(x_0/C_j)}{g_i(x_0) - s(x_0/D_j)} = \frac{f_i(x_0) + s(x_0/C_i)}{g_i(x_0) - s(x_0/D_i)} \right\}$$

$$\sum_{i=1}^p \lambda_i = 1, \mu_j \geq 0, j = 1, \dots, m$$

and $w_i \in C_i, \tilde{w}_i \in D_i, i = 1, \dots, p$,

Such that

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

$$\langle w_i, x_0 \rangle = S(x_0/C_i), \langle \tilde{w}_i, x_0 \rangle = s(x_0/D_i)$$

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

Theorem: 3.2: (KUHN-TUCKER type sufficient condition), support that there exist a feasible solution x_0 for (GFP) and scalars

$$\lambda_i > 0, i = 1, \dots, p, \sum_{i=1}^p \lambda_i = 1, \mu_j \geq 0, j = 1, \dots, m$$

and $w_i \in C_i, \tilde{w}_i \in D_i, i = 1, \dots, p$ such that

i)

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

$$\langle w_i, x_0 \rangle = s(x_0/C_i), \langle \tilde{w}_i, x_0 \rangle = S(x_0/D_i)$$

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

ii) (θ_i, h_i) is (V, ρ_i, σ_j) - convex at x_0 .

Then x_0 is an efficient solution for (GFP)

Proof: Hypothesis (i) implies that

$$0 = \sum_{i=1}^p \lambda_i \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(x_0) \quad (3.1)$$

Since (ϕ_i, h_j) is (V, ρ_i, σ_j) convex at x_0 , we have for all $x \in S$

$$\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} - \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \tilde{w}_i, x_0 \rangle}$$

$$\geq \bar{\alpha}_i(x, x_0) \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) (x-x_0)^t + \rho_i \|\bar{\theta}_i(x, x_0)\|^2$$

and $0 =$

$$-h_j(x_0) \geq \beta_j(x, x_0) \nabla h_j(x_0)(x - x_0)^t + \sigma_j \|\theta_j(x, x_0)\|^2$$

By using $\bar{\alpha}_i(x, x_0) > 0, i = 1, \dots, p$ and

$\beta_j(x, x_0) > 0, j = 1, \dots, m$ we get

$$\begin{aligned} & \frac{1}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x) + \langle w_i, x \rangle}{g(x) - \langle \tilde{w}_i, x \rangle} \right) - \frac{1}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) \\ & \geq \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g_i(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) (x - x_0)^t + \frac{\rho_i \|\bar{\theta}_i(x, x_0)\|^2}{\bar{\alpha}_i(x, x_0)} \end{aligned} \tag{3.2}$$

$$\text{And } 0 \geq \nabla h_j(x_0)(x - x_0)^t + \frac{\sigma_j \|\theta_j(x, x_0)\|^2}{\beta_j(x, x_0)} \tag{3.3}$$

Adding (3.2) and (3.3), we get

$$\begin{aligned} & \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x) + \langle w_i, x \rangle}{g(x) - \langle \tilde{w}_i, x \rangle} \right) - \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) \\ & \geq \left[\sum_{i=1}^p \lambda_i \nabla \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(x_0) \right] (x - x_0)^t \\ & \quad + \sum_{i=1}^p \lambda_i \frac{\rho_i \|\bar{\theta}_i(x, x_0)\|^2}{\bar{\alpha}_i(x, x_0)} + \sum_{j=1}^m \mu_j \frac{\sigma_j \|\theta_j(x, x_0)\|^2}{\beta_j(x, x_0)} \end{aligned}$$

Using (3.1), we have

$$\begin{aligned} & \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x) + \langle w_i, x \rangle}{g(x) - \langle \tilde{w}_i, x \rangle} \right) - \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) \\ & \geq \sum_{i=1}^p \lambda_i \frac{\rho_i \|\bar{\theta}_i(x, x_0)\|^2}{\bar{\alpha}_i(x, x_0)} + \sum_{j=1}^m \mu_j \frac{\sigma_j \|\theta_j(x, x_0)\|^2}{\beta_j(x, x_0)} \end{aligned}$$

As $\sum_{i=1}^p \lambda_i \frac{\rho_i \|\bar{\theta}_i(x, x_0)\|^2}{\bar{\alpha}_i(x, x_0)} \geq 0$ and

$$\sum_{j=1}^m \mu_j \frac{\sigma_j \|\theta_j(x, x_0)\|^2}{\beta_j(x, x_0)} \geq 0 \text{ we get}$$

$$\sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x) + \langle w_i, x \rangle}{g(x) - \langle \tilde{w}_i, x \rangle} \right) - \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right) \geq 0$$

Thus we have

$$\sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \frac{f_i(x) + \langle w_i, x \rangle}{g(x) - \langle \tilde{w}_i, x \rangle} \geq \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle}$$

Suppose that x_0 is not an efficient solution for (GEP), then there exist a feasible solution x for (GFP) and an index Γ such that $\theta_i(x) \leq \theta_i(x_0)$ for any $i \neq \Gamma$ and Φ , where

$$\theta_i(x) = \frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} \text{ for any } i.$$

Since $\lambda_i > 0$ and $\bar{\alpha}_i(x, x_0) > 0, i = 1, \dots, P$, we have

$$\sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \Phi_i(x) < \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \Phi_i(x_0)$$

It follows that one has

$$\sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x) + \langle w_i, x \rangle}{g(x) - \langle \tilde{w}_i, x \rangle} \right) < \sum_{i=1}^p \frac{\lambda_i}{\bar{\alpha}_i(x, x_0)} \left(\frac{f_i(x_0) + \langle w_i, x_0 \rangle}{g(x_0) - \langle \tilde{w}_i, x_0 \rangle} \right)$$

Which contradicts the inequalities (34) and hence x_0 is an efficient solution for (GFP)

4 Mond - Weir type duality:-

We now consider the following Mond-Weir type dual for (GFP) (DGFP) Maximize

$$\max \left\{ \frac{f_i(u) + S(u/C_i)}{g_i(u) - S(u/D_i)} / i = 1, \dots, P \right\}$$

Subject to

$$\sum_{i=1}^p \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(u) = 0 \tag{4.1}$$

$$\begin{aligned} & w_i \in C_i, \langle w_i, u \rangle = S(u/C_i), \tilde{w}_i \in D_i, \\ & \langle \tilde{w}_i, u \rangle = S(u/D_i), i = 1, \dots, m \end{aligned}$$

$$\lambda_i > 0, i = 1, \dots, P, \sum_{i=1}^p \lambda_i = 1, \mu_j \geq 0, j = 1, \dots, m, \sum_{j=1}^m \mu_j h_j(u) = 0$$

Theorem: (4.1): (Weak Duality) Let x be a feasible solution for (GFP) and let $(u, \lambda, \mu, w, \tilde{w})$ be feasible for (DGFP) such that (Φ_i, h_j) is (Φ_i, h_j) is (V, ρ_i, σ_j) - convex at u . then the following cannot hold

$$\left(\frac{f_i(x) + S(x/C_i)}{g_i(x) - S(x/D_i)} \right) < \left(\frac{f_i(u) + S(u/C_i)}{g_i(u) - S(u/D_i)} \right) \tag{4.2}$$

Proof: Suppose that (4.2) holds that is

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

Using

$$\lambda_i > 0, i = 1, \dots, P, \sum_{i=1}^P \lambda_i = 1, \mu_j \geq 0, j = 1, \dots, m$$

we get

$$\sum_{i=1}^P \lambda_i \left(\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} \right) < \sum_{i=1}^P \lambda_i \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right)$$

That is

$$\sum_{i=1}^P \lambda_i \left(\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} \right) - \sum_{i=1}^P \lambda_i \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right) < 0$$

(4.3)

$$\text{and } -\sum_{j=1}^m \mu_j h_j(u) = 0 \tag{4.4}$$

By (v, p, σ) convexity, we have

$$\begin{aligned} & \sum_{i=1}^P \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right) (x-u)^t + \sum_{i=1}^P \lambda_i \frac{\rho_i \|\bar{\theta}_i(x, x_0)\|^2}{\bar{\alpha}_i(x, u)} \\ & \leq \sum_{i=1}^P \lambda_i \left(\frac{f_i(x) + \langle w_i, x \rangle}{g_i(x) - \langle \tilde{w}_i, x \rangle} \right) - \sum_{i=1}^P \lambda_i \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right) < 0 \end{aligned}$$

And

$$\sum_{j=1}^m \mu_j \nabla h_j(u) (x-u)^t + \sum_{j=1}^m \mu_j \frac{\sigma_j \|\theta_j(x, u)\|^2}{\beta_j(x, u)} \leq -\sum_{j=1}^m \mu_j \nabla h_j(u) = 0$$

That is,

$$\sum_{i=1}^P \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right) (x-u)^t + \sum_{i=1}^P \lambda_i \frac{\rho_i \|\bar{\theta}_i(x, u)\|^2}{\bar{\alpha}_i(x, u)} < 0$$

And

$$\sum_{j=1}^m \mu_j \nabla h_j(u) (x-u)^t + \sum_{j=1}^m \mu_j \frac{\sigma_j \|\theta_j(x, u)\|^2}{\beta_j(x, u)} \leq 0$$

By adding the above inequalities, we get

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$$\left[\sum_{i=1}^P \lambda_i \nabla \left(\frac{f_i(u) + \langle w_i, u \rangle}{g_i(u) - \langle \tilde{w}_i, u \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(u) \right] (x-u)^t < 0$$

Which contradicty the dual constraints (4.1). Hence (4.2) cannot hold.

Theorem 4.2:- (Strong Duality) : Let \bar{x} be a weakly efficient solution for (GFP). Then there exist $\bar{\lambda} \in R^P, \bar{\mu} \in R^m$ and $\bar{w} \in C$ such that $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \bar{\tilde{w}})$ is feasible for (DGFP). Moreover, If the weak duality holds, then $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \bar{\tilde{w}})$ is a weakly efficient solution for (DGFP)

Proof:-

Take \bar{x} a wakly efficient solution for (GFP) and suppose that

$0 \notin \text{co} \{ \nabla h_j(\bar{x}) / j = 1, \dots, m \}$. Then there exist

$\bar{\lambda} \in R^P, \bar{\mu} \in R^m$ and

$\bar{w}_i \in C_i, \bar{\tilde{w}} \in D_i, i = 1, \dots, P$

Such that

$$\sum_{i=1}^P \lambda_i \nabla \left(\frac{f_i(\bar{x}) + \langle w_i, \bar{x} \rangle}{g_i(\bar{x}) - \langle \tilde{w}_i, \bar{x} \rangle} \right) + \sum_{j=1}^m \mu_j \nabla h_j(\bar{x}) = 0$$

$$(\bar{w}_i, \bar{x}) = S(\bar{x} / C_i), (\bar{\tilde{w}}, \bar{x}) = S(\bar{x} / D_i)$$

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

$$\bar{\lambda}_i > 0, i = 1, \dots, P, \sum_{i=1}^P \bar{\lambda}_i = 1 \tag{Thus,}$$

$(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \bar{\tilde{w}})$ is a feasible solution for (DGFP).

On the other hand, by weak duality (Theorem 4.1)

$$\max \left\{ \frac{f_i(\bar{x}) + S(\bar{x} / C_i)}{g_i(\bar{x}) - S(\bar{x} / D_i)} / i = 1, \dots, P \right\} \geq \max \left\{ \frac{f_i(u) + S(u / C)}{g_i(u) - S(u / D)} / i = 1, \dots, P \right\}$$

for any feasible solution $(x, \lambda, \mu, w, \tilde{w})$ of (DGFP).

Hence $(\bar{x}, \bar{\lambda}, \bar{\mu}, \bar{w}, \bar{\tilde{w}})$ is a weakly efficient solution for (DGFP).

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