

Higher-Order $(F, \alpha, \beta, \rho, d, E)$ -Convexity in Fractional Programming

Himanshu TIWARI*, Seema MEENA, Deepak KUMAR, D. B. OJHA

Department of Mathematics, Faculty of Science, University of Rajasthan, Jaipur 302004, India

Abstract In this paper we define higher order $(F, \alpha, \beta, \rho, d, E)$ -convex function with respect to E -differentiable function K and obtain optimality conditions for nonlinear programming problem (NP) from the concept of higher order $(F, \alpha, \beta, \rho, d)$ -convexity. Here, we establish Mond-Weir and Wolfe duality for (NP) and utilize these duality in nonlinear fractional programming problem.

Keywords E -convexity; higher order $(F, \alpha, \beta, \rho, d, E)$ -convexity; optimality conditions; duality; fractional programming

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1. Introduction

Applications of generalized convexity cover a broad area in mathematical programming, in which optimality criteria and duality relations make a dominant place. Hanson [1] considered sufficient conditions (Khun Tucker-conditions) for the existence of solution of programming problems with convexity. Then Hanson and Mond [2] obtained these conditions and duality results for generalized convexity. Vial [3] studied weakly and strongly convex sets and defined ρ -convex function. Preda [4] defined (F, ρ) -convex functions and obtained duality results under the assumption of (F, ρ) -convexity. Liang et al. [5] generalized convexity to (F, α, ρ, d) -convexity and founded optimality conditions and duality related results in nonlinear fractional programming. Yuan et al. [6] expanded the concept of (F, α, ρ, d) -convexity to (C, α, ρ, d) -convexity. Gulati and Saini [7] introduced higher order $(F, \alpha, \beta, \rho, d)$ -convexity and applied its concept in fractional programming for obtaining duality results.

A well known class of generalized convexity, namely E -convexity performs a significant role in mathematical programming. Youness [8] gave the concept of E -convexity and designed some results of E -convex functions in programming problem. Then Youness [9, 10] obtained necessary and sufficient optimality conditions for E -convex programming and discussed E -Fritz John and E -KT (E -Khun Tucker) conditions. Chen [11] considered semi E -convex functions and its related some properties. Syau and Lee [12] produced some properties of E -convex functions with the concept of E -quasiconvex functions. Megahed et al. [13] designed a combined interactive

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* Corresponding author

E-mail address: hmtiwari1997@gmail.com (Himanshu TIWARI)

approach for multi-objective E -convex programming. Later, Megahed et al. [14] also defined E -differentiable function and used this definition with KT-conditions in producing optimal solutions of programming problems with E -differentiable function. Then Iqbal et al. [15] defined geodesic E -convex sets, geodesic E -convex functions and E -epigraphs.

2. Definitions and preliminaries

Some definitions and illustrative example, are given:

Definition 2.1 E -convex set. A set $M \subseteq R^n$, n is said to be an E -convex set with respect to an operator $E : R^n \rightarrow R^n$ if

$$tE(x) + (1 - t)E(y) \in M,$$

for each $x, y \in M$ and $0 \leq t \leq 1$ (see [8]).

Definition 2.2 E -convex function. A real valued function $\varphi : M \subseteq R^n \rightarrow R$, R is said to be an E -convex function with respect to an operator $E : R^n \rightarrow R^n$ on M . If M is an E -convex set and for each $x, y \in M$ and $0 \leq t \leq 1$

$$\varphi(tE(x) + (1 - t)E(y)) \leq t\varphi(E(x)) + (1 - t)\varphi(E(y)).$$

If $\varphi(tE(x) + (1 - t)E(y)) \geq t\varphi(E(x)) + (1 - t)\varphi(E(y))$ then φ is called E -concave function on M .

Definition 2.3 A point \bar{x} is an optimal solution of the problem (P) if and only if $\varphi(E(\bar{x})) \leq \varphi(E(x)) \forall x \in M$, M is an E -convex set.

Definition 2.4 Let $E : R^n \rightarrow R^n$ be an operator and φ is an E -convex and E -differentiable function on an E -convex set M , then φ is said to be higher order $(F, \alpha, \beta, \rho, d, E)$ -convex function at \bar{x} on M if for all $x \in M$, then there exists a vector $p \in R^n$, real valued functions $\alpha, \beta : M \times M \rightarrow R^+ - \{0\}$ and a real valued function $d : M \times M \rightarrow R$ and a real number ρ such that

$$\begin{aligned} \varphi(E(x)) - \varphi(E(\bar{x})) \geq & F(E(x), E(\bar{x}); \alpha(x, \bar{x})[\nabla\varphi(E(\bar{x})) + \nabla_p K(E(\bar{x}), p)]) + \\ & \beta(x, \bar{x})(K(E(\bar{x}), p) - \frac{1}{2}p^T \nabla_p K(E(\bar{x}), p)) + \rho d^2(x, \bar{x}). \end{aligned}$$

We consider the following nonlinear programming problem:

$$\begin{aligned} (NP_E) \quad & \text{Minimize } \varphi(E(x)), \\ & \text{Subject to } M = \{x \in R^n : h(E(x)) \leq 0, \quad x \in M\}, \end{aligned}$$

where the function φ and a set M are E -convex with respect to the map $E : R^n \rightarrow R^n$ and the functions $\varphi : M \rightarrow R$ and $h = (h_1, h_2, h_3, \dots, h_m) : M \rightarrow R^m$ are E -differentiable on X . Let $S = \{x \in M : h(E(x)) \leq 0\}$ denote the set of all feasible solutions for (NP_E) .

Definition 2.5 Let $E : R^n \rightarrow R^n$ be an operator and f be E -convex function on an E -convex

set M . The functional $F : M \times M \times R^n \rightarrow R$ is said to be sublinear in the third variable, if for all $x, \bar{x} \in M$.

(i) $F(E(x), E(\bar{x}); \eta_1 + \eta_2) \leq F(E(x), E(\bar{x}); \eta_1) + F(E(x), E(\bar{x}); \eta_2)$ for all $\eta_1, \eta_2 \in R^n$.

(ii) $F(E(x), E(\bar{x}); \alpha a) = \alpha F(E(x), E(\bar{x}); a)$ for all $\alpha \in R_+$ and $a \in R^n$.

From (ii) it is clear that $F(E(x), E(\bar{x}); 0) = 0$.

Based on the concept of the sublinear functional, we now introduce the class of higher-order $(F, \alpha, \beta, \rho, d, E)$ -convex functions as follows:

Let M be an convex open set and $M \subset R^n$. Let $\varphi : M \rightarrow R$, $K : X \times R^n \rightarrow R$ be E -differentiable functions, $F : M \times M \times R^n \rightarrow R$ be a sublinear functional in the third variable and $d : M \times M \rightarrow R$. Further, let $\alpha, \beta : M \times M \rightarrow R_+ \setminus 0$ and $\rho \in R$.

Definition 2.6 Let $E : R^n \rightarrow R^n$ be an operator and f be E -convex function on an E -convex set M . The function φ is said to be higher-order $(F, \alpha, \beta, \rho, d, E)$ -convex at \bar{x} with respect to K , if for all $x \in M$ and $\rho \in R^n$,

$$\begin{aligned} \varphi(E(x)) - \varphi(E(\bar{x})) \geq & F(E(x), E(\bar{x}); \alpha(x, \bar{x})\{\nabla\varphi(E(\bar{x})) + \nabla_p K(\bar{x}, p)\}) + \\ & \beta(x, \bar{x})\{K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p)\} + \rho d^2(x, \bar{x}). \end{aligned}$$

Remark 2.7 Let $E(x) = x$. Then this gives results of [7].

Remark 2.8 Let $K(\bar{x}, p) = 0$.

(i) Then the above definition becomes that of $(F, \alpha, \beta, \rho, d, E)$ -convex function.

(ii) If $\alpha(x, \bar{x}) = 1$, we obtain the definition of (F, ρ, E) -convex function.

(iii) If $\alpha(x, \bar{x}) = 1$, $\rho = 0$ and $F(E(x), E(\bar{x}); \nabla\varphi(E(\bar{x}))) = \zeta^T(E(x), E(\bar{x})\nabla\varphi(E(\bar{x})))$ for a certain map $\zeta : M \times M \rightarrow R^n$, then $(F, \alpha, \beta, \rho, d, E)$ -convexity reduces to the E -convexity.

(iv) If F is E -convex with respect to the third argument, then we obtain the definition of $(F, \alpha, \beta, \rho, d, E)$ -convex function.

Remark 2.9 Let $\beta(x, \bar{x}) = 1$.

(i) If $K(E(\bar{x}), p) = \frac{1}{2}p^T \nabla^2 \varphi(E(\bar{x}))$, then the above inequality reduces to the definition of second order (F, α, ρ, d, E) -convex function. And if $E(\bar{x}) = \bar{x}$ then it shows result of [16].

(ii) $\alpha(x, \bar{x}) = 1$, $\rho = 0$, $K(E(\bar{x}), p) = \frac{1}{2}p^T \nabla^2 \varphi(E(\bar{x}))$ and $F(E(x), E(\bar{x}); a) = \zeta^T(E(x), E(\bar{x})a)$, where $\zeta : M \times M \rightarrow R^n$, the above definition becomes that of ζ - E -convexity. And if $E(\bar{x}) = \bar{x}$, then it shows result of [17].

Proposition 2.10 (Kuhn-Tucker Necessary Optimality Conditions [18]) Let $\bar{x} \in M$ be an optimal solution of (NP_E) and let h satisfy a constraint qualification. Then there exists $\bar{v} \in R^m$ such that

$$\nabla\varphi(E(\bar{x})) + \nabla h(E(\bar{x}))\bar{v} = 0, \quad (2.1)$$

$$\bar{v}^T h(E(\bar{x})) = 0, \quad (2.2)$$

$$\bar{v} \geq 0, h(E(\bar{x})) \leq 0, \quad (2.3)$$

where $\nabla h(E(\bar{x}))$ denotes the $n \times m$ matrix $[\nabla h_1(E(\bar{x})), \nabla h_2(E(\bar{x})), \nabla h_3(E(\bar{x})), \dots, \nabla h_m(E(\bar{x}))]$.

The following example illustrates our results.

Example 2.11 We consider the function $\varphi : M \subseteq R_+ \rightarrow R$ such that $\varphi(x) = x^n - 2x$. If

$$F(x, \bar{x}, \alpha) = \alpha(x - \bar{x}^2) - 3x, \quad d(x, \bar{x}) = x - \bar{x},$$

$$\alpha(x, \bar{x}) = \frac{x + \bar{x}^2 + 1}{3}, \quad \beta(x, \bar{x}) = \frac{x + \bar{x}^2 + 1}{3}$$

and the operator $E(x) = x^2$, then for $\rho = 0$, φ is higher-order (F, α, ρ, d, E) -convex function at $\bar{x} = 0$ with respect to p , $-\infty < p \leq 1$.

3. Sufficient optimality conditions

In this section, we establish Kuhn-Tucker sufficient optimality conditions for (NP_E) under $(F, \alpha, \beta, \rho, d, E)$ -convexity assumptions.

Theorem 3.1 Let $\bar{x} \in M$ and $\bar{v} \in R^m$ satisfy (2.1)–(2.3). If

- (i) φ is higher-order $(F, \alpha, \beta, \rho_1, d, E)$ -convex at \bar{x} with respect to K ,
- (ii) $\bar{v}^T h$ is higher-order $(F, \alpha, \beta, \rho_2, d, E)$ -convex at \bar{x} with respect to $-K$, and
- (iii) $\rho_1 + \rho_2 \geq 0$,

then \bar{x} is an optimal solution of the problem (NP_E) .

Proof Let $\bar{x} \in M$ since φ is a higher-order $(F, \alpha, \beta, \rho_1, d, E)$ -convex at \bar{x} with respect to K , for all $x \in M$, we have

$$\varphi(E(x)) - \varphi(E(\bar{x})) \geq F(E(x), E(\bar{x}); \alpha(x, \bar{x})[\nabla \varphi(E(\bar{x})) + \nabla_P K(E(\bar{x}), p)]) + \beta(x, \bar{x})(K(E(\bar{x}), p) - \frac{1}{2}p^T \nabla_p K(E(\bar{x}), p)) + \rho_1 d^2(x, \bar{x}). \quad (3.1)$$

Using (2.1), we get

$$\varphi(E(x)) - \varphi(E(\bar{x})) \geq F(E(x), E(\bar{x}); \alpha(x, \bar{x})[\nabla h(E(\bar{x}))\bar{v} + \nabla_P K(E(\bar{x}), p)]) + \beta(x, \bar{x})(K(E(\bar{x}), p) - \frac{1}{2}p^T \nabla_p K(E(\bar{x}), p)) + \rho_1 d^2(x, \bar{x}). \quad (3.2)$$

Also $\bar{v}^T h$ is higher-order $(F, \alpha, \beta, \rho_2, d, E)$ -convex at \bar{x} with respect to $-K$. Therefore,

$$\bar{v}^T h(E(x)) - \bar{v}^T h(E(\bar{x})) \geq F(E(x), E(\bar{x}); \alpha(x, \bar{x})[\nabla \bar{v}^T h(E(\bar{x})) - \nabla_P K(E(\bar{x}), p)]) - \beta(x, \bar{x})(K(E(\bar{x}), p) - \frac{1}{2}p^T \nabla_p K(E(\bar{x}), p)) + \rho_2 d^2(x, \bar{x}). \quad (3.3)$$

Since $\bar{v}^T h(E(\bar{x})) = 0$, $\bar{v} \geq 0$ and $h(E(x)) < 0$, we get

$$0 \geq F(E(x), E(\bar{x}); \alpha(x, \bar{x})[\nabla \bar{v}^T h(E(\bar{x})) - \nabla_P K(E(\bar{x}), p)]) - \beta(x, \bar{x})(K(E(\bar{x}), p) - \frac{1}{2}p^T \nabla_p K(E(\bar{x}), p)) + \rho_2 d^2(x, \bar{x}). \quad (3.4)$$

Adding the inequalities (3.2) and (3.4), we obtain

$$\varphi(E(x)) - \varphi(E(\bar{x})) \geq (\rho_1 + \rho_2)d^2(x, \bar{x}),$$

which by Hypothesis (iii) implies, $\varphi(E(x)) \geq \varphi(E(\bar{x}))$. Hence \bar{x} is an optimal solution of the problem (NP_E) . \square

4. Mond Weir duality

In this section, we establish weak and strong duality theorems for the following Mond Weir dual (MD_E) for (NP_E) :

$$(MD) \text{ Maximize } \varphi(E(u)),$$

$$\text{Subject to } \nabla\varphi(E(u)) + \nabla h(E(u))v = 0, \quad (4.1)$$

$$v^T h(E(u)) \geq 0, \quad (4.2)$$

$$u \in X, \quad v \geq 0, \quad v \in R^m. \quad (4.3)$$

Theorem 4.1 (Weak Duality) *Let x and (u, v) be feasible solutions of (NP_E) and (MD_E) , respectively. Let*

(i) φ be higher-order $(F, \alpha, \beta, \rho_1, d, E)$ -convex at \bar{x} with respect to K .

(ii) $v^T h$ be higher-order $(F, \alpha, \beta, \rho_2, d, E)$ -convex at u with respect to $-K$, and

(iii) $\rho_1 + \rho_2 \geq 0$.

Then $\varphi(E(x)) \geq \varphi(E(u))$ is an optimal solution of the problem (NP_E) .

Proof By Hypothesis (i), we have

$$\begin{aligned} \varphi(E(x)) - \varphi(E(u)) &\geq F(E(x), E(u); \alpha(x, \bar{u})[\nabla\varphi(E(u)) + \nabla_P K(E(u), p)]) + \\ &\quad \beta(x, u)(K(E(u), p) - p^T \nabla_p K(E(u), p)) + \rho_1 d^2(E(x), E(u)). \end{aligned} \quad (4.4)$$

Also Hypothesis (ii) yields

$$\begin{aligned} v^T h(E(x)) - v^T h(E(u)) &\geq F(E(x), E(u); \alpha(x, \bar{u})[\nabla v^T h(E(u)) - \nabla_P K(E(u), p)]) - \\ &\quad \beta(x, u)(K(E(u), p) - p^T \nabla_p K(E(u), p)) + \rho_2 d^2(x, u). \end{aligned}$$

By (4.2), (4.3) and $h(E(x)) \leq 0$ it follows that

$$\begin{aligned} 0 &\geq F(E(x), E(u); \alpha(x, \bar{u})[\nabla v^T h(E(u)) - \nabla_P K(E(u), p)]) - \\ &\quad \beta(x, u)(K(E(u), p) - p^T \nabla_p K(E(u), p)) + \rho_2 d^2(x, u). \end{aligned} \quad (4.5)$$

Adding the inequalities (4.4), (4.5) and applying the properties of sublinear functional, we obtain

$$\begin{aligned} \varphi(E(x)) - \varphi(E(u)) &\geq F(E(x), E(u); \alpha(x, \bar{u})[\nabla\varphi(E(u)) + \nabla v^T h(E(u))]) + \\ &\quad \rho_1 d^2(x, u) + \rho_2 d^2(x, u) \end{aligned}$$

which in view of (4.1) implies

$$\varphi(E(x)) - \varphi(E(u)) \geq (\rho_1 + \rho_2)d^2(x, u).$$

Using Hypothesis (iii) in the above inequality, we get

$$\varphi(E(x)) \geq \varphi(E(u)). \quad \square$$

Theorem 4.2 (Strong Duality) *Let \bar{x} be an optimal solution of the problem (NP_E) and let h satisfy a constraint qualification. Further, let Theorem 4.1 hold for the feasible solution \bar{x} of (NP_E) and all feasible solutions (u, v) of (MD_E) . Then there exists a $\bar{v} \in R_+^m$ such that (\bar{x}, \bar{v}) is an optimal solution of (MD_E) .*

Proof Since \bar{x} is an optimal solution for the problem (NP_E) and h satisfies a constraint qualification, by Proposition 2.10 there exists a $\bar{v} \in R_+^m$ such that the Kuhn-Tucker conditions, (2.1)–(2.3) hold. Hence (\bar{x}, \bar{v}) is feasible for (MD_E) .

Now let (u, v) be any feasible solution of (MD_E) . Then by weak duality (Theorem 4.1), we have

$$\varphi(\bar{x}) \geq \varphi(u).$$

Therefore, (\bar{x}, \bar{v}) is an optimal solution of (MD_E) . \square

5. Higher-order $(F, \alpha, \beta, \rho, d, E)$ -convexity in fractional programming

Let Y be an E -convex set with respect to the map $E : R \rightarrow R$ and function $\varphi : Y \rightarrow R$ be defined as

$$\varphi = \frac{f(E(x))}{g(E(x))},$$

where $f, g : Y \rightarrow R$ is defined on Y with $f(E(x)) \geq 0$ and $g(E(x)) > 0$. Then we consider the following fractional programming problem (FP_E) from the nonlinear programming problem (NP_E)

$$\begin{aligned} & \text{Min} \frac{f(E(x))}{g(E(x))}, \\ & \text{sub to } h(E(x)) \leq 0, \quad x \in X. \end{aligned}$$

Then we obtain some following results under the assumptions of higher-order $(F, \alpha, \beta, \rho, d, E)$ -convexity of the ratio $\frac{f(E(x))}{g(E(x))}$.

Theorem 5.1 *Let $f(x)$ and $-g(x)$ be two higher-order $(F, \alpha, \beta, \rho, d, E)$ -convex functions at \bar{x} with respect to the same function K . Then the ratio function $\frac{f(x)}{g(x)}$ is also a higher-order $(F, \alpha, \beta, \rho, d, E)$ -convex function at \bar{x} with respect \bar{K} , where*

$$\bar{\alpha}(x, \bar{x}) = \alpha(x, \bar{x}) \frac{g(E(\bar{x}))}{g(E(x))},$$

$$\begin{aligned}\bar{\beta}(x, \bar{x}) &= \beta(x, \bar{x}) \frac{g(E(\bar{x}))}{g(E(x))}, \\ \bar{K}(E(\bar{x}), p) &= \left[\frac{1}{g(E(\bar{x}))} + \frac{f(E(\bar{x}))}{g^2(E(\bar{x}))} \right] K(E(\bar{x}), p), \\ \bar{d}(x, \bar{x}) &= \left[\frac{1}{g(E(x))} + \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} \right]^{1/2} d(x, \bar{x}).\end{aligned}$$

Proof Since $f(x)$ and $-g(x)$ are higher-order $(F, \alpha, \beta, \rho, d, E)$ -convex functions at \bar{x} with respect to the function K , we have

$$\begin{aligned}f(E(x)) - f(E(\bar{x})) &\geq F(x, \bar{x}; \alpha(x, \bar{x}) \{ \nabla f(E(\bar{x})) + \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad \beta(x, \bar{x}) \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} + \rho d^2(x, \bar{x})\end{aligned}$$

and

$$\begin{aligned}-g(E(x)) + g(E(\bar{x})) &\geq F(x, \bar{x}; \alpha(x, \bar{x}) \{ \nabla g(E(\bar{x})) + \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad \beta(x, \bar{x}) \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} + \rho d^2(x, \bar{x}),\end{aligned}$$

also

$$\begin{aligned}\frac{f(E(x))}{g(E(x))} - \frac{f(E(\bar{x}))}{g(E(\bar{x}))} &= \frac{1}{g(E(x))} [f(E(x)) - f(E(\bar{x}))] + \\ &\quad \frac{f(E(\bar{x}))}{g(E(x))g(E(\bar{x}))} [-g(E(x)) + g(E(\bar{x}))].\end{aligned}$$

By sub-linearity of function F and above inequalities, we have

$$\begin{aligned}\frac{f(E(x))}{g(E(x))} - \frac{f(E(\bar{x}))}{g(E(\bar{x}))} &\geq \frac{1}{g(E(x))} F(x, \bar{x}; \alpha(x, \bar{x}) \{ \nabla f(E(\bar{x})) + \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad \frac{1}{g(E(x))} (\beta(x, \bar{x}) \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} + \rho d^2(x, \bar{x})) + \\ &\quad \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} F(x, \bar{x}; \alpha(x, \bar{x}) \{ -\nabla g(E(\bar{x})) + \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} (\beta(x, \bar{x}) \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} + \rho d^2(x, \bar{x})) \\ &= F(x, \bar{x}; \frac{\alpha(x, \bar{x})}{g(E(x))} \{ \nabla f(E(\bar{x})) + \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad F(x, \bar{x}; \alpha(x, \bar{x}) \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} \{ -\nabla g(E(\bar{x})) + \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad \beta(x, \bar{x}) \left[\frac{1}{g(E(x))} + \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} \right] \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} + \\ &\quad \rho \left[\frac{1}{g(E(x))} + \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} \right] d^2(x, \bar{x}) \\ &= F(x, \bar{x}; \alpha(x, \bar{x}) \frac{g(E(\bar{x}))}{g(E(x))} \{ \nabla \frac{f(E(\bar{x}))}{g(E(\bar{x}))} + \left[\frac{1}{g(E(x))} + \frac{f(E(\bar{x}))}{g^2(E(\bar{x}))} \right] \nabla_p K(E(\bar{x}), p) \}) + \\ &\quad \beta(x, \bar{x}) \frac{g(E(\bar{x}))}{g(E(x))} \left[\frac{1}{g(E(\bar{x}))} + \frac{f(E(\bar{x}))}{g^2(E(\bar{x}))} \right] \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} +\end{aligned}$$

$$\rho \left[\frac{1}{g(E(x))} + \frac{f(E(\bar{x}))}{g(E(\bar{x}))g(E(x))} \right] d^2(x, \bar{x}).$$

Therefore,

$$\begin{aligned} \frac{f(E(x))}{g(E(x))} - \frac{f(E(\bar{x}))}{g(E(\bar{x}))} &\geq F(x, \bar{x}; \alpha(x, \bar{x}) \left[\frac{f(E(\bar{x}))}{g(E(\bar{x}))} + \nabla_p K(E(\bar{x}), p) \right] + \\ &\quad \bar{\beta}(x, \bar{x}) \{ K(E(\bar{x}), p) - p^T \nabla_p K(E(\bar{x}), p) \} + \rho d^2(x, \bar{x}). \end{aligned}$$

This shows that the ratio function $\frac{f(x)}{g(x)}$ is a higher-order $(F, \alpha, \beta, \rho, d, E)$ -convex function at \bar{x} with respect to \bar{K} . It follows from the relation between (FP_E) and its Mond-Weir dual (MFD_E)

$$\begin{aligned} &\text{Max } \frac{f(E(x))}{g(E(x))}, \\ &\text{subject to } \nabla \left(\frac{f(E(x))}{g(E(x))} \right) + \nabla h(E(x))v = 0, \\ &v^T h(E(u)) \geq 0, \\ &u \in M, v \geq 0, v \in R^n. \quad \square \end{aligned}$$

Theorem 5.2 (Weak Duality) *Let $E(x)$ and $(E(u), E(v))$ be feasible solutions of (FP_E) and (MFD_E) , respectively, and*

(i) *$f(x)$ and $-g(x)$ be two higher-order $(F, \alpha, \beta, \rho_1, d, E)$ -convex functions at u with respect to K .*

(ii) *$f(x)$ and $v^T h$ be higher-order $(F, \alpha, \beta, \rho_2, d, E)$ -convex functions at u with respect to $-\bar{K}$, where $\bar{\alpha}, \bar{\beta}, \bar{K}$ and \bar{d} are as given in Theorem 5.1, and*

(iii) *$\rho_1 + \rho_2 \geq 0$. Then*

$$\frac{f(E(x))}{g(E(x))} \geq \frac{f(E(u))}{g(E(u))}.$$

Theorem 5.3 (Strong Duality) *Let $E(\bar{x})$ be an optimal solution of (FP_E) and let h satisfy a constraint qualification. Further, if Theorem 5.2 holds for the feasible solution $E(\bar{x})$ of (FP_E) and all feasible solutions $(E(u), E(v))$ of (MFD_E) , then there is a $\bar{v} \in R_+^n$ such that $(E(\bar{x}), E(\bar{v}))$ is an optimal solution of (MFD_E) .*

6. Wolfe duality

The Wolfe dual (NP_E) and (FP_E) are, respectively,

$$\begin{aligned} &\text{Max } \varphi(E(u)) + v^t h(E(u)), \\ &\text{subject to } \nabla \varphi(E(u)) + \nabla h(E(u))v = 0, \\ &u \in X, v \geq 0, v \in R^n \end{aligned}$$

and

$$\text{Max } \frac{f(E(u))}{g(E(u))},$$

$$\begin{aligned} & \text{subject to } \nabla\left(\frac{f(E(u))}{g(E(u))}\right) + \nabla h(E(u))v = 0, \\ & u \in X, v \geq 0, v \in R^n. \end{aligned}$$

Now we consider duality relations for the primal problem (NP_E) , (WD_E) and their Wolfe, respectively, in higher-order $(F, \alpha, \beta, \rho, d, E)$ -convexity sense.

Theorem 6.1 (Weak Duality) *Let $E(x)$ and $(E(u), E(v))$ be feasible solutions of (NP_E) and (WD_E) , respectively, and*

- (i) φ be higher-order $(F, \alpha, \beta, \rho_1, d, E)$ -convex functions at u with respect to K .
- (ii) $v^t h$ be higher-order $(F, \alpha, \beta, \rho_2, d, E)$ -convex functions at u with respect to $-K$.
- (iii) $\rho_1 + \rho_2 \geq 0$.

Then $\varphi(E(x)) \geq \varphi(E(u)) + v^T h(E(u))$.

Theorem 6.2 (Strong Duality) *Let $E(\bar{x})$ be an optimal solution of (NP_E) and let h satisfy a constraint qualification. Further, if Theorem 6.1 holds for the feasible solution $E(\bar{x})$ of (NP_E) and all feasible solutions $(E(u), E(v))$ of (WD_E) , then there is a $\bar{v} \in R_+^n$ such that $(E(\bar{x}), E(\bar{v}))$ is an optimal solution of (WD_E) and values of optimal objective functions of (NP_E) and (WD_E) are equal.*

Theorem 6.3 (Weak Duality) *Let $E(x)$ and $(E(u), E(v))$ be feasible solutions of (FP_E) and (WFD_E) , respectively, and*

- (i) $f(x)$ and $-g(x)$ be two higher-order $(F, \alpha, \beta, \rho_1, d, E)$ -convex functions at u with respect to K ,
- (ii) $v^t h$ be higher-order $(F, \alpha, \beta, \rho_2, d, E)$ -convex at u with respect to $-\bar{K}$, where $\bar{\alpha}, \bar{\beta}, \bar{K}$ and \bar{d} are as given in Theorem 5.1, and
- (iii) $\rho_1 + \rho_2 \geq 0$.

Then

$$\frac{f(E(x))}{g(E(x))} \geq \frac{f(E(u))}{g(E(u))} + v^T h(E(u)).$$

Theorem 6.4 (Strong Duality) *Let $E(\bar{x})$ be an optimal solution of (FP_E) and let h satisfy a constraint qualification. Further, if Theorem 6.3 holds for the feasible solution $E(\bar{x})$ of (FP_E) and all feasible solutions $(E(u), E(v))$ of (WFD_E) , then there is a $\bar{v} \in R_+^n$ such that $(E(\bar{x}), E(\bar{v}))$ is an optimal solution of (WFD_E) and values of optimal objective functions of (FP_E) and (WFD_E) are equal.*

7. Conclusions

This work generates a new form of E -convexity from the concept of higher-order $(F, \alpha, \beta, \rho_2, d)$ -convexity. If E is an identity map, then this work makes a correspondence to [7] and generalises the result related to the optimality criteria and duality of [7] for E -convexity in fractional programming.

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