

# GENERALIZED G-SADDLE POINT AND GENERALIZE G-WOLFE DUALITY WITH UNIVEXITY

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## Abstract

In this paper, we consider generalized G-Saddle point. Different generalizations of G-Wolfe duality with respective generalized univexity will be derived in the context of Antczak. Strong and weak duality theorems will be derived in this context.

**Key words:** G-Saddle Point, Duality, Univexity.

## 1. Introduction

Early in the development of game theory, it was observed that matrix games were equivalent to a dual pair of linear programs (Karlin [17], Charnes [11] and Cottle [12]) Recently, Kawaguchi and Mayurama [18] were formulated dual linear program.

Recently, Corley considered a two-person bi-matrix vector-valued game in which strategy spaces are mixed and introduced the concept of solution of this game. He has also established the necessary and sufficient optimality conditions for the solution of such a game. Chandra and Durga Prasad [10] considered a constrained two-person zero-sum game with vector pay-off and discussed its relation with a pair of multiobjective programming problems. More recently, Singh and Rueda [26] generalized the work of Chandra and Durga Prasad [10] replacing differentiability by sub-differentiability. Also, they were investigated the connection between an equilibrium point of a vector-valued constrained game and a generalized saddle point.

They had shown the relationship between certain convex-concave vector valued games and a pair of nonlinear multiobjective programming problems. Recently, Khan and Hanson [19], has given a new treatment on ratio invexity for a mathematical programming problem. They

established sufficient optimality conditions and duality results for an invex fractional programming problem.

## 2. Notations and Definitions:

In section 2, will discuss basic definitions and notaris, which will needed in the sequel.

Any function  $f : R \rightarrow R$  is known as strictly increasing if, for all  $x, y, \varepsilon, R, x < y$ , implies  $f(x_1) < (f, y)$

Definitions 2.2 [1] Let  $S$  be a non-empty, open subset of  $R^n$  and the function  $f : X \rightarrow R$  be a differentiable function defined on  $X$ . If  $\exists$  a differentiable real-valued strictly increasing function on  $G$ : If  $f : X \rightarrow R$  and a vector-valued function  $\eta : X \times X \rightarrow R^n \ni$  for  $X \in X(x \neq n)$ , we have  $G(f(x)) - G(f(u)) \geq G'(f(u)) \nabla f(x) \eta^T(x, u)$  then the function  $f$  is called  $G$ -invex at  $u \in X$  on  $X$  w.r.t.  $\eta$ .

We will define  $d_1 - v - \rho$ -univexity as follows.

Definition 2.3 [1] Let  $S$  be a non-empty, open subset of  $R^n$  and the function  $f : X \rightarrow R$  be a differentiable function defined on  $X$ . If  $\exists$  a differentiable real-valued strictly increasing function on  $G$ : If  $f : X \rightarrow R$  and a vector-valued function  $\eta : X \times X \rightarrow R^n \ni$  for  $X \in X(x \neq n)$ . Then the function is said to be  $d_1 - v - \rho$ -univexity if.

$$b(x, u)G(f(x)) - G(f(u)) \geq G^T(f(x)) \nabla f(x) \eta^T(x, u) + (\rho \square \theta x, y) \square^2$$

## 3. Problem formulation

In this section, we consider the following nonlinear mathematical programming problem.

$$(NP) \quad \min f(x) = (f_1(x), \dots, f_n(x))$$

$$\text{subject to } g_j(x) \leq 0, \quad j \in J = \{1, 2, \dots, m\}$$

where  $S$  is a non-empty open subset of  $\mathbb{R}^n$  and  $f_i: S \rightarrow \mathbb{R}$ ,  $j \in J, i \in I$  are in general continuously differentiable function.

In general, set of all feasible solutions is denoted by

$$F_1 = \{x \in S : g_j(x) \leq 0, j \in J\}$$

In the sequel, the set of indices of the set of active constraints is denoted by  $J_1(u) = \{j \in T : g_j(u) = 0\}$ .

Let us consider a suitable definition of the so-called G-Lagrangian function for the chosen nonlinear multi objective mathematical programming problem as:

$$L_G(x; \lambda_1, \mu_1) = \lambda_1 G_{f_1}(f_1(x)) + \sum_{j=1}^m \mu_j G_{g_j}(g_j(x))$$

where  $G_{f_i}: I_{f_i}(S) \rightarrow \mathbb{R}$  and  $G_{g_j}: I_{g_j}(S) \rightarrow \mathbb{R}$  are generally differentiable real valued strictly increasing functions.

Let us introduce a generalized definition of a G-Saddle point for the generalized G-Lagrangian function for the nonlinear multi objective mathematical programming problem.

**Definition 3.1:** Suppose  $(\tilde{x}, \tilde{\lambda}, \tilde{\mu}) \in D \times \mathbb{R} + \mathbb{R}_+^m$  is a point is called a Generalized G-Saddle point for the nonlinear multi objective mathematical programming problem if the following hold:

$$i) L_G(\tilde{x}, \tilde{\lambda}, \mu) \leq L_G(\tilde{x}, \tilde{\lambda}, \tilde{\mu}_1),$$

$$\text{and (ii) } L_G(\tilde{x}, \tilde{\lambda}_1, \tilde{\mu}_1) \leq L_G(\tilde{x}, \tilde{\lambda}_1, \tilde{\mu}_1),$$

Let us recall the following Fritz-John necessary optimality conditions for a given mathematical programming problem.

**Theorem 3.1** (Necessary optimality conditions According to Antczak[1])

Let  $\tilde{x} \in S$  be an optimal point in a mathematical programming problem (MP). Then, the following G-Fritz-John necessary optimality condition are satisfied:

$$\tilde{\lambda}_1, G_f^T(f(\tilde{x}))\nabla f(\tilde{x}) + \sum_{j=1}^m \tilde{\mu}_j, G_{g_j}^T(g_j(\tilde{x}))\nabla_{g_j}(\tilde{x}) = 0 \quad (3.2)$$

$$\tilde{\mu}_1 \left[ G_{g_j}(g_j(x)) - G_{g_j}(g_j(\tilde{x})) \leq 0, j \in J, \forall x \in S \right] \quad (3.3)$$

$$\text{and } \tilde{\lambda}_1 \geq 0, \tilde{\mu}_1 \geq 0, (\tilde{\lambda}_1, \tilde{\mu}_1) \neq (0, 0) \quad (3.4)$$

Here  $G_j$  is a differentiable real-valued strictly increasing function defined on  $I_f(S)$ , and  $G_{g_j}, j \in J_1$ , is also a differentiable real-valued strictly increasing function defined on  $I_{g_j}(S)$ .

**Definition 3.2 :** Suppose the equilibrium the point  $(\tilde{x}, \tilde{\lambda}, \tilde{\mu}_1) \in S \times R \times R^n$  satisfies the above G-Fritz-John necessary optimality condition (3.2) – (3.4), then the equilibrium point is known as G-Fritz-John equilibrium for the nonlinear multi objective mathematical programming problem (MP).

Let us consider the Antczak [1] G-type constraint qualification known as generalized G-type constraint qualification.

**Definition 3.3:**

The nonlinear multi objective mathematical programming (MP) is said to satisfy the G-type constraint qualification at  $\tilde{x} \in S$  if  $g_j, j \in J(\tilde{x})$ , are  $G_{g_j}$ -univex w.r. to the same  $\eta$  and  $\theta$  at  $\tilde{x}$  and  $S$  and more over  $\exists \tilde{x} \in S \ni$

$$G_{g_j}(g_j(x)) < G_{g_j}(g_j(\tilde{x})), J \in J(\tilde{x})$$

According to Antczak [1] we use the following the men in the sequel.

**Theorem 3.1**

Suppose  $\tilde{x} \in S$  is an optimal point in a nonlinear multi objective mathematical problem (MP) and the generalized G-type constraint qualification is to be satisfied at  $\tilde{x}$ . Then, the following generalized G-K-KK-Tucker necessary optimality conditions are fulfilled.

$$G_f^T(f_i(\tilde{x}))\nabla f(\tilde{x})\eta^T(x, \tilde{x}) + \rho \square \theta(x, \tilde{x}) \square^2 + \sum_{j=1}^m \tilde{\mu}_j, G_{g_j}^T(g_j(\tilde{x})) \times \nabla_{g_j}(\tilde{x}) = 0 \quad (4.5)$$

$$b(x, \tilde{x}) \tilde{\mu}_1^l \left[ G_{g_j}(g_j(x)) - G_{g_j}(g_j(\tilde{x})) \right] \leq 0 \quad j \in J_1, x \in S \quad (4.6)$$

$$\text{and } \tilde{\mu}_1 \geq 0 \quad (4.7)$$

hence  $G_f$  is a differentiable real – valmed strictly increasing function, which is defined an

$$I_f(S), G_{g_j}, j \in J \text{ defined on } I_{g_j}(S) \text{ and } \sum_{i \in J(\tilde{x})} \left[ G_{g_j}^T(g_j \tilde{x}) \right]^2 \neq 0.$$

We will establish the equivalence between the optimal point  $\tilde{x}$  and the generalized G-equivalence point.  $(\tilde{x}, \tilde{\lambda}, \tilde{\mu}) \in S \times R \times R^m$  in a nonlinear multi objective programming problem (MP).

### Theorem 3.2:

Suppose  $(\tilde{x}, \tilde{\lambda}, \tilde{\mu}) \in S \times R_+ \times R_+^m$  is a generalized saddle point of the generalized Lagrangian function for the multi objective mathematical programming problem (MP) and the corresponding generalized G-type constraint qualification satisfied at the point  $\tilde{x}$ .

Further, assume that  $G_f$  and  $G_{g_j}$  are real-valued strictly increasing function an  $I_f(S)$  and  $I_{g_j}(S), G_{g_j}(0) = 0$  for some  $j \in J_1$ , and  $\sum_{j \in J(g)} \left[ G_{g_j}^T(g_j(\tilde{x})) \right]^2 \neq 0$ . Then  $\tilde{x}$  is optimal solution in problem (MP).

**Proof:** This result can be proved by contradiction.

Let us assume that  $(\tilde{x}, \tilde{\lambda}, \tilde{\mu}) \in S \times R_+ \times R_+^m$  be a saddle point for the chosen problem (MP).

By definition, we have, for any  $\tilde{\mu}_1 \in R_+^m$   $L_G(\tilde{x}, \tilde{\lambda}, \tilde{\mu}_1) \leq L_G(\tilde{x}, \tilde{\lambda}, \tilde{\mu}_1)$

But, by the definition of the generalized G – Lagrangian function, we set

$$\lambda_1, G_f(f_i(x)) + \sum_{j=1}^m \mu_j G_{g_j}(g_j(x))$$

$$\leq_1 \tilde{\lambda} G_f(f_1(\tilde{x})) + \sum_{j=1}^m \mu_j G_{g_j}(g_j(\tilde{x}))$$

which implies that

$$\sum_{j=1}^m \mu_j^l G_{g_j}(g_j(x)) \leq \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(\tilde{x}))$$

Let us assume that  $\mu_1 = 0$  in the above,

we set

$$\sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(\tilde{x})) \geq 0 \quad (3.8)$$

By the feasibility of  $\tilde{x}$  in the chosen problem (mp), that follows  $g_j(\tilde{x}) \leq 0, j \in J_1$ . But, by assumption,  $G_{g_j}, j \in J_1$  is a differentiable real-valued strictly (monotonic) functions defined the set  $I_{g_j}(S)$ , and  $G_{g_j}(0) = 0$  for some  $j \in J_1$ .

For any  $j \in J$  we have

$$G_{g_j}(g_j(\tilde{x})) \leq G_{g_j}(0) = 0$$

But, by  $\tilde{\mu}_j \in \mathbb{R}_+^m$ , we set

$$\sum_{i=1}^m \tilde{\mu}_i G_{g_i}(g_i(\tilde{x})) \leq 0 \quad (3.9)$$

Let us compare equations (3.8) and (3.9),

$$\sum_{i=1}^m \tilde{\mu}_i G_{g_i}(g_i(\tilde{x})) = 0 \quad (3.10)$$

On the contrary, let  $\tilde{x}$  is not optimal in (mp) i.e.,  $\tilde{x} \in S \ni$

$$f_i(\tilde{x}) < f_i(\tilde{x}) \quad i = 1, 2, \dots, n.$$

#### 4. Duality Results

Here, we discuss a generalized type duality for the chosen multi objective nonlinear programming. Denoting it as a generalized form as

$$L_G(u, \tilde{\mu}_1) = L_G(u, \tilde{\lambda}, \tilde{\mu})$$

Let us consider the corresponding Wolfe type dual is as

$$(G\text{-MWD}) \max L_G(u, \tilde{\mu}_1) = G_{f_i}(f_i/u) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(u))$$

subject to:

$$G_j^1(f_i(u)) \nabla f(u) \eta^T(x, u) + \rho \theta(x, u)^2$$

$$\sum_{j=1}^m \tilde{\mu}_j G_{g_j}^1(g_j(u)) \times \nabla g_j(u) = 0$$

and  $u \in S, \tilde{\mu} \geq 0$

Here  $G_{f_i}$  and  $G_{g_j}$ ,  $j \in J_1$  have their usual meanings.

Let us denote the set of feasible solutions as:

$$W_1 = \left\{ (u, \tilde{\mu}_1) \in S \times \mathbb{R}^m : G_{f_i}^1(f_i(u)) \nabla f(u) \eta^T(x, u) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}^1(g_j(u), \nabla g_j(u) = 0, \tilde{\mu}_1) \right\}$$

Consequently  $\gamma_1 = \{u \in S : (u, \tilde{\mu}_1) \in W_1\}$ .

**Theorem 4.1** (G-Wolfe weak duality),

Let  $x$  and  $(u, \tilde{\mu}_1)$  be any feasible solutions in (MFP) and (G-MWD), respectively, moreover, assume that the and fixed  $\mu_1^1 \geq 0$ , then generalized G-Lagrangian function is  $d_1 - \alpha - v - \rho$ -univexity at  $u$  on FUY w.r. to  $\eta$  and  $\theta$ ,  $G_{g_j}(0) = 0$ , for

$j \in J_1$ . Then,  $G_{f_i}(f_i(x)) \geq G_{f_i}(f_i(u)) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(u))$ .

**Proof:**

Let us assume that  $x$  and  $(x, \tilde{\mu}_1)$  be any two feasible solutions in problem (MP) and (G-MWD), respectively.

By using the assumption that the Langrangian function and by the definition of is  $d_1 - v - p$ - univexity at the point  $u$  on SUY with respect to  $\eta$  and  $\theta$ , and also, by using definition 2.2, we obtain

$$\begin{aligned} & G^T f_i(f_i(x)) + \sum_{j=1}^m \tilde{\mu}_j G^T g_j(g_j(x)) - G_{f_i}(f_i(u)) - \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(u)) \\ & \geq \left[ G_{f_i}^T \left( f_i(u) \nabla f(u) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}^T(g_j(u)) \times \nabla g_j(u) \right) \eta^T(x, u) + \rho \square \theta(x, u) \right]^2 \end{aligned}$$

But from the feasibility of  $(u, \tilde{\mu}_1)$  in the above problem, we get

$$\begin{aligned} & G_{f_i}(f_i(x)) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(x)) - G_{f_i}(f_i(u)) - \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(u)) \eta^T(x, u) \\ & + \rho \square \theta(x, u) \square^2 \end{aligned} \quad (4.17)$$

According to

the feasibility of  $x$  in the chosen problem (MP), it follows that  $g_j(x) \leq 0, j \in J_1$ .

Since  $G_{g_j}, j \in J_1$  is a strictly increasing (monotonic) function, which is defined on  $I_{g_j}(S)$  and

$G_{g_j}(0) = 0$ , for  $j \in J_1$ , then, we have

$$G_{g_j}(g_j(x)) \leq G_{g_j}(0) = 0$$

$\Rightarrow$  by  $\tilde{\mu} \geq 0, j \in T$ , we have

$$\sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(x)) \eta^T(x, y) + \rho \square \theta(x, y) \square^2 \leq 0$$

From (4.17) and (4.18) one can obtain

$$b(x, y) (G_{f_i}(f_i(x)) \geq G_{f_i}(f_i(n))) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(u)) \eta^T(x, y) + \rho \square \theta(x, y) \square^2$$



Hence the result is proved.

**Theorem 4.2** (G-Wolfe Strong Dual)

Suppose  $\tilde{\mu}$  is an optimal solution problem (MP) and the generalized G-type constraint qualification is satisfied at  $\tilde{\mu}_1$ . Now,  $\exists \tilde{\mu}_j \in \mathbb{R}_+^m \in (\tilde{x}, \tilde{\mu}_j)$  is feasible for (G-MWD) and the corresponding objective functions of the two problem (MP) and (G-MWD) are equal at these points, also, by hypothesis,  $(\tilde{x}, \tilde{\mu}_j)$  is optimal in (G-MWD).

**Proof:** Since  $\tilde{x}$  is an optimal solution in (MP) and the generalized G-type constraint qualifications is also satisfied at  $\tilde{x}$  then the corresponding (above stated) generalized G-KT necessary optimality conditions are satisfied at  $\tilde{x}$ .

Then, the corresponding feasibility  $(\tilde{x}, \tilde{\mu}_j)$  in the above generalized (G-MWD) follows on from the generalized G-KKT optimality (necessary) condition (3.5) – (3.7)

By using the previous weak duality theorem (4.1), we obtain

$$b(\tilde{x}, u) \left( G(f_i \tilde{x}) - G_{f_i}(f_i(u)) \geq \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(u)) \right) \eta^T(\tilde{x}, u) + \rho \|\theta(\tilde{x}, u)\|^2$$

which holds for all  $(u, \tilde{\mu}_j) \in w$

Since  $\tilde{x}$  is an optimal solution in the considered problem (MP) and  $G_{g_j}(0)=0$  for some  $j \in J_1$ , and by applying generalized G-KKT-optimality conditions, one can obtain

$$\begin{aligned} & G_{f_i}(f_i(\tilde{x})) + \sum_{j=1}^m \tilde{\mu}_j G_{g_j}(g_j(\tilde{x})) \eta^T(\tilde{x}, u) + \rho \|\theta(\tilde{x}, u)\|^2 \\ & \geq G_{f_i}(f_i(u)) + \sum_{j=1}^m G_{f_i}(f_i(u)) + \eta^T(\tilde{x}, u) + \rho \|\theta(\tilde{x}, u)\|^2 \end{aligned}$$

which holds for all  $(u, \tilde{\mu}_j) \in w_1$

Hence,  $(\tilde{x}, \tilde{\mu}_j)$  is an optimal in Generalized (G-MWD).

## Conclusion

Here we derived different duality theorems for G-Saddle points with respect to generalized  $d_1$ - $v$ - $\rho$ -univexity of Antczak type.

## References

- [1] Antczak, T 2013. G-saddle point criteria and G-Wolfe duality in differentiate mathematical programming. *Journal of Information and Optimization Sciences*, 63-85.
- [2] Antczak, T. 2001.  $(p, r)$  -invex sets and functions. *Journal of Mathematical Analysis and Applications*, 80: 545–550.
- [3] Antczak, T. 2004. An  $\eta$ -approximation approach for nonlinear mathematical programming problems involving invex functions. *Numerical Functional Analysis and Optimization*, 25(5–6): 423–438.
- [4] Antczak, T. 2005.  $r$  -pre-invexity and  $r$  -invexity in mathematical programming. *Computers and Mathematics with Applications*, 50: 551–566.
- [5] Antczak, T. 2007. New optimality conditions and duality results of G-type in differentiable mathematical programming. *Nonlinear Analysis, Theory, Methods and Applications*, 66: 1617–1632.
- [6] Antczak, T. 2007. Saddle point criteria in an  $\eta$  -approximation method for nonlinear mathematical programming problems involving invex functions. *Journal of Optimization, Theory and Applications*, 132(1): 71–87.
- [7] Antczak, T. 2008. G-pre-invex functions in mathematical programming. *Journal of Computational and Applied Mathematics*, 217: 212–226.
- [8] Bazaraa, M.S., Sherali, H.D. and Shetty, C.M. 1991. *Nonlinear Programming: Theory and Algorithms*, New York: John Wiley and Sons.
- [9] Ben-Israel, A. and Mond, B. 1986. What is invexity?. *Journal of Australian Mathematical Society, Ser. B*, 28: 1–9.

- [10] Chandra, S. and Durga Prasad, M.V. “Constrained vector valued games and multiobjective programming”, OPSEARCH, 29 (1992), 1-10.
- [11] Charnes, A. “Constrained games and linear programming”, Proc. Nat. Acad. Sci. (U.S.A.), 30 (1953), 639-641.
- [12] Cottle, R.W. “An infinite game with convex-concave pay-off kernel”, Research report No. ORC 63-19(RN-2), Operations Research Centre, University of California, Berkeley, 1963.
- [13] Craven, B.D. 1981. Invex functions and constrained local minima. Bulletin of the Australian Mathematical Society, 24: 357–366.
- [14] Hanson, M.A. 1981. On sufficiency of the Kuhn-Tucker conditions. Journal of Mathematical Analysis and Applications, 80: 545–550.
- [15] Hanson, M.A. and Mond, B. 1987. Necessary and sufficient conditions in constrained optimization. Mathematical Programming, 37: 51–58.
- [16] Jeyakumar, V. 1988. Equivalence of saddle-points and optima, duality for a class of non-smooth non-convex problems. Journal of Mathematical Analysis and Applications, 130: 334–343.
- [17] Karlin, S. “Mathematical methods and theory in games, programming and economics”, Vol: I, II (1959), Addison-Wsley, Reading Mass.
- [18] Kawaguchi, T. and Mayurama, Y. “A note on minimax (maximin) programming”, Management Sci., 22 (1976), 670-676.
- [19] Khan, Z.A. and Hanson, M.A. “On ration invexity in mathematical programming” , Journ. Of Math. Anal. and Appl. 205 (1997), 330-336.
- [20] Klinger, A. and Mangasarian, O.L. 1968. Logarithmic convexity and geometric programming. Journal of Mathematical Analysis and Applications, 24: 388–408.
- [21] Mangasarian, O.L. 1969. Nonlinear Programming, New York: McGraw-Hill.

- [22] Martin, D.H. 1985. The essence of invexity. *Journal of Optimization, Theory and Applications*, 42: 65–76.
- [23] Pini, R. 1991. Invexity and generalized convexity. *Optimization*, 22: 513–525.
- [24] Rockafellar, R.T. 1970. *Convex Analysis*, Princeton, New Jersey: Princeton University Press.
- [25] Rueda, N.G. and Hanson, M.A. 1988. Optimality criteria in mathematical programming involving generalized invexity. *Journal of Mathematical Analysis and Applications*, 130: 375–385.
- [26] Singh, C. and Rueda, N. “Constrained vector valued games and generalized multiobjective minimax programming”, *OPSEARCH*, 31 (1994), 144-154
- [27] Weir, T. and Jeyakumar, V. 1988. A class of nonconvex functions and mathematical programming. *Bulletin of the Australian Mathematical Society*, 38: 177–189.
- [28] Wolfe, P. 1961. A duality theorem for nonlinear programming. *Quarterly of Applied Mathematics*, 19: 239–244.

