

Solution of NLPP when constraints are not all equality constraints.

Kuhn-Tucker Necessary Conditions for the optimality of the objective function in a GNLPP.

Let us consider the GNLPP

$$\begin{aligned} \max. z &= f(x) & x &= (x_1, x_2, \dots, x_n) \in R^n \\ \text{s.t.} & & & \\ & g_i(x) & \leq & b_i \quad i=1, 2, \dots, m \end{aligned}$$

where,  $b_i$ 's are constants.

Let  $h_i(x) = g_i(x) - b_i \leq 0$

Introducing slack variables  $s_1, s_2, \dots, s_m$  ( $s_i ; i=1, 2, \dots, m$ ), we have

$$h_i(x) + s_i^2 = 0$$

Thus, the given NLPP with inequalities constraints reduces to equality constraints as follows

$$\begin{aligned} \max. z &= f(x) \\ \text{s.t.} & \\ & h_i(x) + s_i^2 = 0 \\ & x \geq 0. \end{aligned}$$

and hence it can be solved by using Lagrangian Multipliers  $\lambda_1, \lambda_2, \dots, \lambda_m$

let us define the Lagrangian function

$$L(x, s, \lambda) = f(x) - \sum_{i=1}^m \lambda_i [h_i(x) + s_i^2]$$

where,

$$x = (x_1, x_2, \dots, x_n) \in R^n$$

$$\lambda = (\lambda_1, \lambda_2, \dots, \lambda_m) \in R^m$$

$$s = (s_1, s_2, \dots, s_m) \in R^m$$

let  $L, f$  and  $h_i$  are all differentiable partially w.r.t.  $x_1, x_2, \dots, x_n, \lambda_1, \lambda_2, \dots, \lambda_m, s_1, s_2, \dots, s_m$

The necessary conditions for the stationary points are

$$\frac{\partial L}{\partial x_j} = \frac{\partial f}{\partial x_j} - \sum_{i=1}^m \lambda_i \frac{\partial h_i}{\partial x_j} = 0 \quad \text{--- (1)}$$

$\forall j = 1, 2, \dots, n$

$$\frac{\partial L}{\partial \lambda_i} = - [h_i(x) + s_i^2] = 0 \quad ; \quad i = 1, 2, \dots, m \quad \text{--- (2)}$$

$$\frac{\partial L}{\partial s_i} = - 2s_i \lambda_i = 0 \quad ; \quad i = 1, 2, \dots, m \quad \text{--- (3)}$$

From (3), we have

either  $s_i = 0$  or  $\lambda_i = 0$

If  $s_i = 0$

Then (2)  $\Rightarrow h_i(x) = 0$

$\therefore \lambda_i = 0$  or  $s_i = 0$

$\Rightarrow \lambda_i = 0$  or  $h_i(x) = 0$  ——— (4)

$\therefore \lambda_i h_i(x) = 0$

$\because s_i^2 \geq 0$

(2)  $\Rightarrow h_i(x) \leq 0$

when  $h_i(x) < 0$

(4)  $\Rightarrow \lambda_i = 0$  and <sup>when</sup>  $\lambda_i > 0, h_i(x) = 0$

$\therefore$  (4)  $\Rightarrow h_i(x) = 0 \Rightarrow \lambda_i$  is unrestricted in sign.

If  $\lambda_i \neq 0$  then  $s_i = 0$

(2)  $\Rightarrow h_i(x) = g_i(x) - b_i = 0$

i.e.  $g_i(x) = b_i$

Hence Kuhn-Tucker necessary conditions for the point  $x$  to be a point of maximum for  $f(x)$ , subject to  $h_i(x) = g_i(x) - b_i \leq 0$  are

$$\frac{\partial f}{\partial x_j} - \sum_{i=1}^m \lambda_i \frac{\partial h_i}{\partial x_j} = 0 \quad \forall j=1,2,3,\dots,n$$

$$\lambda_i h_i(x) = 0$$

$$h_i(x) \leq 0 \quad \text{and} \quad \lambda_i \geq 0 \quad i=1,2,\dots,m$$

Similarly, the Kuhn-Tucker necessary condition for the point  $x$  to be a minimum of  $f(x)$ , subject to  $h_i(x) = g_i(x) - b_i \geq 0$  are

$$\frac{\partial f}{\partial x_j} - \sum_{i=1}^m \lambda_i \frac{\partial h_i}{\partial x_j} = 0 \quad \forall j=1,2,\dots,n$$

$$\lambda_i h_i(x) = 0$$

$$h_i(x) \geq 0 \quad \text{and} \quad \lambda_i \geq 0 \quad i=1,2,\dots,m$$

Kuhn-Tucker sufficient cond<sup>ns</sup> for the optimality of the objective function of a GNLP with inequality cond<sup>ns</sup>.

① The Kuhn-Tucker necessary cond<sup>ns</sup> for NLP,  $\max. z = f(x) ; x \in R^n$   
s.t.  
 $h_i(x) = g_i(x) - b_i \leq 0 \quad i=1,2,\dots,m$   
 $x \geq 0$

are also the sufficient cond<sup>ns</sup> for maximum of  $f(x)$  if

- i)  $f(x)$  is concave
- ii)  $h_i(x)$  (i.e.  $g_i(x)$ ) are convex fun<sup>ns</sup> of  $x$   
i.e.  $-h_i(x)$  are also concave fun<sup>ns</sup> of  $x$

② The Kuhn-Tucker N/C for NLP,  
 $\min f(x)$ .  
s.t.  
 $h_i(x) = g_i(x) - b_i \geq 0 \quad i=1,2,\dots,m$   
 $x \geq 0$ .

are also the sufficient cond<sup>ns</sup> for minimum of  $f(x)$  if

1)  $f(x)$  is convex

2)  $h_i(x)$  are also ~~convex~~ <sup>concave</sup> fun<sup>ns</sup> of  $x$ .

ie.  $-h_i(x)$  are also convex fun<sup>ns</sup> of  $x$ .

(For more details refer page 839, 840 of R.K. Gupta),