

## البحث عن مسار Direct Search method

## Hooke & Jeeves method:

This method consists of two phases:-

- a. **Exploration Search phase**, in this step we establish direction & Improvement.
  - b. **Pattern Move**, which extracts the current solution vector another point in the solution space.

The procedure is as follows:

- Choose an initial base point  $x^\circ = (x_1^\circ + x_2^\circ + \dots + x_n^\circ)$  & an initial step vector  $p = (\Delta x_1 + \Delta x_2 + \dots + \Delta x_n)$
  - Carry out an exploration about  $x^\circ$  as indicated :
    - Evaluate the objective function  $f(x^\circ)$
    - Each variable is now changed in turn by adding the step length and evaluate the function if the function success , replace  $x_i^\circ$  by  $x_i^\circ + \Delta x_i$  ,  
if not try  $x_i^\circ - \Delta x_i$  ,  
if neither step gives a success , leaves  $x_i^\circ$  unchanged & considered all n variables.  
We have a new base point  $x^1$ .
    - If  $x^1 = x^\circ$  the exploration is repeated with reduced step length -

مقدار الزيادة  $x_1$  و  $x_2$  يجب أن تكون  $\Delta$  متساوية

- d. If  $x^1 \neq x^\circ$  we make a pattern move.

3. Pattern move procedure is as follows:

  - move from the base point  $x^1$  in the direction  $x^1 - x^\circ$  & evaluate the function at the pattern move point.  

$$x^2 = x^\circ + 2(x^1 - x^\circ) \Rightarrow x^2 = 2x^1 - x^\circ$$
 call this base point 2
  - Continue exploration

4. Terminate the process when the step size < tolerance.

$$\Delta x_i \leftarrow (\text{tolerance})$$

Example1: Min Z =  $3x_1^2 + x_2^2 - 12x_1 - 8x_2$

Start with an initial value  $x^0 = (1, 1)$  and initial step size  $p = (0.5, 0.5)$ .

**Solution:**

<i>Step</i>	<i>Computation</i>	$X_1$	$X_2$	$f(X_1, X_2)$	<i>Remark</i>
<b>0</b>	<i>Initial</i>	1	1	-16	<i>Initial value</i>
<b>1</b>	<i>Exploration</i>	1.5	1	-18.25	<i>Success</i>
		1.5	1.5	-21	<i>Success</i>

**Base 1 (1.5, 1.5) , Set 1 (1, 1)**

$$x_1^2 = 2(1.5) - 1 = 2$$

<i>2</i>	<i>Pattern Move</i>	<i>2</i>	<i>2</i>	<i>-24</i>	<i>Success</i>
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$$x^3 = 2 + 0.5 = 2.5, P(2.5, 2)$$

**Base 2 (-2 -2)      Set 1(1 1)**

$$x^3 = 2 - 0.5 = 1.5, P(1.5, 2)$$

$$x^3 \equiv 2 + 0.5 \equiv 2.5, P(2, 2.5)$$

<b>3</b>	<i>Exploration</i>	<b>2.5</b>	<b>2</b>	<b>-23.25</b>	<i>Failure</i>
		<b>1.5</b>	<b>2</b>	<b>-23.25</b>	<i>Failure</i>
		<b>2</b>	<b>2.5</b>	<b>-25.75</b>	<i>Success</i>

**Base 3 (2, 2.5) , Set 2 (1.5, 1.5)**

$$\cancel{x_1^4} = 2(2) - 1.5 = 2.5$$

$$x^4 = 2(2.5) - 1.5 = 3.5$$

<b>4</b>	<i>Pattern Move</i>	2.5	3.5	-27	<i>Success</i>
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**Base 4 (2.5, 3.5) → Set 2 (1.5, 1.5)**

<b>5</b>	<i>Exploration</i>	<b>3</b>	<b>3.5</b>	<b>-24</b>	<i>Failure</i>
		<b>2</b>	<b>3.5</b>	<b>-27.75</b>	<i>Success</i>
		<b>2</b>	<b>4</b>	<b>-28</b>	<i>Success</i>

Base 5 (2,4), Set 3 (2,2.5)

<b>6</b>	<i>Pattern Move</i>	<b>2</b>	<b>5.5</b>	<b>-25.75</b>	<i>Failure</i>
	<i>Exploration</i>	<b>2.5</b>	<b>5.5</b>	<b>-25</b>	<i>Failure</i>
		<b>1.5</b>	<b>5.5</b>	<b>-25</b>	<i>Failure</i>
		<b>2</b>	<b>6</b>	<b>-24</b>	<i>Failure</i>

## The Method of Rotating Coordinates (Resonbrock Method)

## Resonbrock unconstrained procedure

To minimize the objective function  $f(x_1, x_2, \dots, x_n)$  the algorithm of the procedure on the following steps:

1. A starting point  $x_1^\circ, x_2^\circ, \dots, x_n^\circ$  and initial step size  $\lambda_i, i = 1, 2, \dots, n$  are selected and the objective function evaluated.
  2. The first variable  $x_1$  is stepped a distance  $\lambda_1$  parallel to the axis & the function evaluated.

If the value of the objective function decreased , the move is termed a success &  $\lambda_i$  increased by a factor  $\alpha (\alpha \geq 1)$ .

If the value of the objective function increased , the move is termed a failure &  $\lambda_i$  decreased by a factor  $\beta(0 < \beta < 1)$ & The direction of movement reversed.

The value of  $\alpha$  &  $\beta$  recommended by Rosenborck are  $\alpha = 3$  &  $\beta = 0.5$ .

3. The next variable  $x_i, i = 1, 2, \dots, n$  is in turn stepped a distance  $\lambda_i$  parallel to the axis. The same acceleration or deceleration in step 2 are applied for all variables in consecutive repetitive sequence until one success & one failure have been encountered at least in all  $n$  direction. i.e. continue the search sequentially along the direction  $S_1^j, S_2^j, \dots, S_i^j, \dots, S_n^j$ , until at least one step has been successful & one step has failed in each of the  $n$ -direction.

4. Compute the new set of direction  $S_1^{j+1}, \dots, S_i^{j+1}, \dots, S_n^{j+1}$  for use in next  $(j+1)^{th}$

Stage of minimization by using the gram-Schmidt orthogonalization procedure.

- a. Compute a set of independent directions  $p_1, p_2, \dots, p_i, \dots, p_n$  as

$$p_{n,n} = \begin{bmatrix} p_1 & p_2 & \dots & p_n \end{bmatrix}$$

$$= \begin{bmatrix} S_1^j, S_2^j, \dots, S_n^j \end{bmatrix} \begin{bmatrix} A_1 & 0 & \dots & 0 \\ A_2 & A_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_n & A_n & \dots & A_n \end{bmatrix}$$

In which

$A_i$  = The algebraic sum of all the successful step length in the corresponding direction

$$S_i^j, i=1,2,\dots,n$$

$P_1$  = The vector joining the starting point & the final point obtained after the sequence of the searches in the  $(j)^{th}$  stage.

$P_2, P_3, \dots, P_n$  = The algebraic sum of the successful step length in the all directions except the first one, & so on these linearly independent vector  $P_1, P_2, \dots, P_n$  can be used to generate a new set of orthogonal directions.

b. Set  $D_1^j = P_1^j$

With  $S_1^j = \frac{D_1^j}{\sqrt{D_1^{(j)T} D_1^j}}$  *Constan*

C. Compute  $D_i^j = P_i^j - \sum_{m=1}^{i-1} \left[ P_{m+1}^{(j)T} S_m^j S_m^j \right]$

With  $S_i^j = \frac{D_i^j}{\sqrt{D_i^{(j)T} D_i^j}}$

- Take the best point obtained in the present stage , & repeat the same procedure of searching from step 2 on words.

$$\text{i.e. } \quad new \overrightarrow{x_{L,i}^j} = old \overrightarrow{x_{L,i}^j} + \lambda_i \overrightarrow{S_{L,i}^j}$$

where:

L = variable index, L = 1,2,.....,n

i = direction index, I = 1,2,.....,n

$j$  = stage index.

6. The procedure terminates when the convergence criterion is satisfied.

Example: Min  $f(x) = x_1 - x_2 + 2x_1^2 + 2x_1x_2 + x_2^2$

## Initial base

$$x = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \& f(x) = 0$$

$$S_1^0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, S_1^0 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \lambda = \begin{bmatrix} 0.8 \\ 0.8 \end{bmatrix}, \beta = 0.5 \& \alpha = 3$$

**Solution:**

## Stage 1:

$$[x_1]_{new} = [x]_{old} + \lambda_1 [S_1]$$

$$\left[ x_1 \right]_{new} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + 0.8 \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.8 \\ 0 \end{bmatrix} \Rightarrow f(0.8, 0) = 2.08 \text{ (failure)}$$

$$\begin{bmatrix} x_2 \end{bmatrix}_{new} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + 0.8 \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0.8 \end{bmatrix} \Rightarrow f(0, 0.8) = -0.16 (\text{Success})$$

<i>point</i>	$X_1$	$X_2$	$\lambda_1$	$\lambda_2$	$f(x)$	<i>Remark</i>
0	0	0	-	-	0	initial
1	0.8	0	0.8	-	2.08	failure
2	0	0.8	-	0.8	-0.16	success
3	-0.4	0.8	-0.4	-	-0.88	success
4	-0.4	3.2	-	2.4	4.4	failure
5	-1.6	0.8	-1.2	-	0.8	failure

We have at least one failure & one success in each direction  $S_1^\circ, S_2^\circ$

Note: New base point  $x = \begin{bmatrix} -0.4 \\ 0.8 \end{bmatrix}$  &  $f(x) = -0.88$

$$A_1 = \sum \lambda_1 @ Success = -0.4$$

$$A_2 = \sum \lambda_2 @ Success = 0.8$$

Stage 2: New set of search direction  $S^1$

$$P_{2x2}^1 = \begin{bmatrix} P_1^1 & P_2^1 \end{bmatrix} = \begin{bmatrix} S_1^\circ & S_2^\circ \end{bmatrix} \begin{bmatrix} A_1 & 0 \\ A_2 & A_2 \end{bmatrix}$$

$$P_{2x2}^1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -0.4 & 0 \\ 0.8 & 0.8 \end{bmatrix} = \begin{bmatrix} -0.4 & 0 \\ 0.8 & 0.8 \end{bmatrix}$$

$$\therefore P_1^1 = \begin{bmatrix} -0.4 \\ 0.8 \end{bmatrix} \& P_2^1 = \begin{bmatrix} 0 \\ 0.8 \end{bmatrix}$$

$$D_1^1 = P_1^1 = \begin{bmatrix} -0.4 \\ 0.8 \end{bmatrix}$$

$$S_1^1 = \frac{D_1^1}{\sqrt{D_1^{1T} \cdot D_1^1}} = \frac{\begin{bmatrix} -0.4 \\ 0.8 \end{bmatrix}}{\sqrt{(0.4)^2 + (0.8)^2}} = \begin{bmatrix} -0.447 \\ 0.894 \end{bmatrix}$$

$$D_i^j = P_i^j - \sum_{m=1}^{i-1} \left[ \left\{ P_{m+1}^{(j)T} S_m^j \right\} S_m^j \right]$$

$$D_2^1 = P_2^1 - \sum_{m=1}^{2-1} \left[ \left\{ P_2^{1T} S_m^1 \right\} S_m^1 \right] = \begin{bmatrix} 0 \\ 0.8 \end{bmatrix} - \left( \begin{bmatrix} 0 & 0.8 \end{bmatrix} \begin{bmatrix} -0.447 \\ 0.894 \end{bmatrix} \right) \begin{bmatrix} -0.447 \\ 0.894 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ 0.8 \end{bmatrix} - \begin{bmatrix} 0*(-0.447) + 0.8*(0.894) \\ 0.894 \end{bmatrix} = \begin{bmatrix} 0 \\ 0.8 \end{bmatrix} - \begin{bmatrix} -0.320 \\ 0.639 \end{bmatrix} = \begin{bmatrix} 0.320 \\ 0.160 \end{bmatrix}$$

$$S_2^1 = \frac{D_2^1}{\sqrt{D_2^{IT} \cdot D_2^1}} = \frac{\begin{bmatrix} 0.32 \\ 0.16 \end{bmatrix}}{\sqrt{(0.32)^2 + (0.16)^2}} = \begin{bmatrix} 0.894 \\ 0.447 \end{bmatrix}$$

$$\text{Due to } \lambda_1 \quad \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{new}} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{old}} + \lambda_1 \begin{bmatrix} -0.447 \\ 0.894 \end{bmatrix} \quad S_1^1$$

$$\text{Due to } \lambda_2 \quad \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{new}} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{old}} + \lambda_2 \begin{bmatrix} 0.894 \\ 0.447 \end{bmatrix} \quad S_2^1$$

<i>point</i>	$\lambda_1$	$\lambda_2$	$X_1$	$X_2$	$f(x)$	<i>Remark</i>
0	-	-	-0.4	0.8	-0.88	Base Point
1	0.8	-	-0.758	1.515	-1.125	success
2	-	0.8	-0.042	1.873	1.439	failure
3	2.4	-	-7.831	3.662	1.212	failure
4	-	-0.4	-1.116	1.337	-1.159	success
5	-1.2	-	-0.579	0.263	0.0499	failure
6	-	-1.2	-2.189	0.8	3.731	failure

We have at least one failure & one success in each direction  $S_1^1, S_2^1$

Note: New base point  $x = \begin{bmatrix} -1.116 \\ 1.337 \end{bmatrix}$  &  $f(x) = -1.159$

$$A_1 = \sum \lambda_i @ Success = 0.8$$

$$A_2 = \sum \lambda_2 @ Success = -0.4$$

Stage 3: New set of search direction  $S^2$

$$P_{2x2}^2 = \begin{bmatrix} P_1^2 & P_2^2 \end{bmatrix} = \begin{bmatrix} S_1^1 & S_2^1 \end{bmatrix} \begin{bmatrix} A_1 & 0 \\ A_2 & A_2 \end{bmatrix}$$

$$P_{2x2}^2 = \begin{bmatrix} -0.447 & 0.894 \\ 0.894 & 0.447 \end{bmatrix} \begin{bmatrix} 0.8 & 0 \\ -0.4 & -0.4 \end{bmatrix} = \begin{bmatrix} -0.7152 & -0.3576 \\ 0.5364 & -0.1788 \end{bmatrix}$$

$$\therefore P_1^2 = \begin{bmatrix} -0.7152 \\ 0.5364 \end{bmatrix} \& P_2^2 = \begin{bmatrix} -0.3576 \\ -0.1788 \end{bmatrix}$$

$$D_1^2 = P_1^2 = \begin{bmatrix} -0.7152 \\ 0.5364 \end{bmatrix}$$

$$S_1^2 = \frac{D_1^2}{\sqrt{D_1^{2T} D_1^2}} = \frac{\begin{bmatrix} -0.7152 \\ 0.5364 \end{bmatrix}}{\sqrt{(0.7152)^2 + (0.5364)^2}} = \begin{bmatrix} -0.8 \\ 0.6 \end{bmatrix}$$

$$D_2^2 = P_2^2 - \left( \left\{ P_2^{2T} S_1^2 \right\} S_1^2 \right) = \begin{bmatrix} -0.3576 \\ -0.1788 \end{bmatrix} - \left( \begin{bmatrix} -0.3576 & -0.1788 \end{bmatrix} \begin{bmatrix} -0.8 \\ 0.6 \end{bmatrix} \right) \begin{bmatrix} -0.8 \\ 0.6 \end{bmatrix} = \begin{bmatrix} -0.2146 \\ -0.2861 \end{bmatrix}$$

$$S_2^2 = \frac{D_2^2}{\sqrt{D_2^{2T} D_2^2}} = \frac{\begin{bmatrix} -0.2146 \\ -0.2861 \end{bmatrix}}{\sqrt{(0.2146)^2 + (0.2861)^2}} = \begin{bmatrix} -0.6 \\ -0.8 \end{bmatrix}$$

$$\text{Due to } \lambda_1 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{new}} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{old}} + \lambda_1 \begin{bmatrix} -0.8 \\ 0.6 \end{bmatrix}$$

$$\text{Due to } \lambda_2 \quad \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{new}} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{old}} + \lambda_2 \begin{bmatrix} -0.6 \\ -0.8 \end{bmatrix}$$

<i>point</i>	$\lambda_1$	$\lambda_2$	$X_1$	$X_2$	$f(x)$	<i>Remark</i>
0	-	-	-1.116	1.337	-1.159	Base Point
1	0.8	-	-1.756	1.817	-0.487	failure
2	-	0.8	-1.596	0.697	1.062	failure
3	-0.4	-	-0.796	1.097	-1.169	success
4	-	-0.4	-0.556	1.417	-0.922	failure
5	-1.2	-	0.164	0.377	0.108	failure
6	-	0.2	-0.416	0.937	-1.014	failure
7	0.6	-	-1.276	1.457	-1.072	failure
8	-	-0.1	-0.736	1.177	-1.177	success
9	-0.3	-	-0.496	0.997	-0.996	failure
10	-	-0.3	-0.556	1.417	-0.992	failure

We have at least one failure & one success in each direction  $S_1^2, S_2^2$

Note: New base point  $x = \begin{bmatrix} -0.736 \\ 1.177 \end{bmatrix}$  &  $f(x) = -1.177$

$$A_1 = \sum \lambda_1 @ Success = -0.4$$

$$A_2 = \sum \lambda_2 @ Success = -0.1$$

Stage 4: New set of search direction  $S^3$

$$P_{2x2}^3 = \begin{bmatrix} P_1^3 & P_2^3 \end{bmatrix} = \begin{bmatrix} S_1^2 & S_2^2 \end{bmatrix} \begin{bmatrix} A_1 & 0 \\ A_2 & A_2 \end{bmatrix}$$

$$P_{2x2}^3 = \begin{bmatrix} -0.8 & -0.6 \\ 0.6 & -0.8 \end{bmatrix} \begin{bmatrix} -0.4 & 0 \\ -0.1 & -0.1 \end{bmatrix} = \begin{bmatrix} 0.38 & 0.06 \\ -0.16 & 0.08 \end{bmatrix}$$

$$\therefore P_1^3 = \begin{bmatrix} 0.38 \\ -0.16 \end{bmatrix} \& P_2^3 = \begin{bmatrix} 0.06 \\ 0.08 \end{bmatrix}$$

$$D_1^3 = P_1^3 = \begin{bmatrix} 0.38 \\ -0.16 \end{bmatrix}$$

$$S_1^3 = \frac{D_1^3}{\sqrt{D_1^{3T} \cdot D_1^3}} = \frac{\begin{bmatrix} 0.38 \\ -0.16 \end{bmatrix}}{\sqrt{(0.38)^2 + (0.16)^2}} = \begin{bmatrix} 0.922 \\ -0.388 \end{bmatrix}$$

$$D_2^3 = P_2^3 - \left( \left\{ P_2^{3T} S_1^3 \right\} S_1^3 \right) = \begin{bmatrix} 0.06 \\ 0.08 \end{bmatrix} - \left( \begin{bmatrix} 0.06 & 0.08 \end{bmatrix} \begin{bmatrix} 0.922 \\ -0.388 \end{bmatrix} \right) \begin{bmatrix} 0.922 \\ -0.388 \end{bmatrix} = \begin{bmatrix} 0.037 \\ 0.089 \end{bmatrix}$$

$$S_2^3 = \frac{D_2^3}{\sqrt{D_2^{3T} D_2^3}} = \frac{\begin{bmatrix} 0.037 \\ 0.089 \end{bmatrix}}{\sqrt{(0.037)^2 + (0.089)^2}} = \begin{bmatrix} 0.384 \\ -0.923 \end{bmatrix}$$

$$\text{Due to } \lambda_1 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{new}} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{old}} + \lambda_1 \begin{bmatrix} 0.922 \\ -0.388 \end{bmatrix}$$

$$\text{Due to } \lambda_2 \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{new}} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{\text{old}} + \lambda_2 \begin{bmatrix} 0.384 \\ -0.923 \end{bmatrix}$$

<i>point</i>	$\lambda_1$	$\lambda_2$	$X_1$	$X_2$	$f(x)$	<i>Remark</i>
0	-	-	-0.736	1.177	-1.177	Base Point
1	0.8	-	0.002	0.866		
2	-	0.8				

Continue !!!!!

## خلاصة طريقة (Resonbrock)

١- نبدأ (Initial value) لقيم  $(x_1 \& x_2)$  ونعتبرها (Base) أي قاعدة للحل ثم نجد منها قيمة جديدة لـ  $(x_1 \& x_2)$  التالية وكل انحدار (Slop) و( $\lambda$ ) في الخطوة صفر لا تؤخذ قيمة ( $\lambda$ )

ثم نحسب قيمة ( $x$ ) الجديدة وفق المعادلات التالية  $[x_1]_{new} = [x]_{old} + \lambda_1 [S_1]$  ونعرض في  $Z$

٢- نعرض قيم  $(x_1 \& x_2)$  الجديدة في المعادلة لإيجاد قيمة  $Z$  فإذا نحوت قيمة  $(x_1 \& x_2)$  في الخطوة هذه تأخذ هذه القيم كقاعدة (Base) للترجك للخطوة التالية. أما قيمة  $(\lambda)$  الجديدة =  $(3\lambda_1)$ . أما إذا فشلت فنرجع إلى القيمة السابقة (التي حققت نجاح سابق) ونعتبرها (Base) أما قيمة  $(\lambda)$  الجديدة =  $(-0.5\lambda_1)$ .

٣- لغرض التوقف المحاولة (Stage) يجب أن يتحقق على الأقل لكل نجاح فشل نفس (x).

٤- تحسب قيمة  $(A_1)$  أي المجموع الجبري لـ  $(A_1)$  التي تمثل قيمة  $\lambda$  التي أدت إلى النجاح وـ  $(A_2)$  ونقارن بينهما لتجد أيهما يعطي القيمة المثلثي (أمثل قيمة).

عندما تستخدم في إيجاد القيم الجديدة والتي تعتبر  $(Base)$  لـ  $(x_1 \& x_2)$  التالية:

٥- في أي مرحلة يجب أن تحسب الانحدارات الجديدة (New Set of Search Direction).

# Non-Linear programming with Inequality Constraints

The general nonlinear problems is defined as

$$\left( \begin{array}{c} \max \\ \min \end{array} \right) Z = f(x), \quad x = (x_1, x_2, \dots, x_n)$$

**Subject to:**

$$\begin{aligned} g_i(x) &\leq 0 & (i = 1, 2, \dots, r) \\ g_i(x) &\geq 0 & (i = r+1, \dots, p) \\ g_i(x) &= 0 & (i = p+1, \dots, m) \end{aligned}$$

The inequality constraints may be converted into equation by adding nonlinear slack variable.

Now, the Lagrange function may be written as:

$$L(x, \lambda, s) = f(x) - \sum_{i=1}^r \lambda_i (g_i(x) + s_i^2) - \sum_{i=r+1}^p \lambda_i (g_i(x) - s_i^2) - \sum_{i=p+1}^m \lambda_i (g_i(x))$$

A necessary condition for optimality, that be non-negative (non-positive) for max (min) problems.

- For direct search method:

The success & failure depend not only on the value of the objective function but on the constraints.

Example:  $\text{Max } Z = x_1 + x_2$

Subject to:  $x_1^2 + x_2^2 \leq 20$

$$(x_1 = x_2 = \Delta x_1 = \Delta x_2 = 1)$$

Using Hooks & Jeeves method?

$$\text{Max. } Z = x_1 + x_2, \text{ subject to } g(x_1, x_2) = x_1^2 + x_2^2 - 20 \leq 0$$

<i>Step</i>	<i>Computation</i>	$X_1$	$X_2$	$Z$	$g(X_1, X_2)$	<i>Remark</i>
<b>0</b>	<i>Initial</i>	<b>1</b>	<b>1</b>	<b>2</b>	<b>-18</b>	<i>Initial value</i>
<b>1</b>	<i>Exploration</i>	2	1	3	-15	<i>Success</i>
		2	2	4	-13	<i>Success</i>

**Base 1 (2, 2) , Set 1 (1, 1)**

<b>2</b>	<b><i>Pattern move</i></b>	<b>3</b>	<b>3</b>	<b>6</b>	<b>-2</b>	<b><i>Success</i></b>
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## **Base 2 (3,3) , Set 1 (1,1)**

<b>3</b>	<i>Exploration</i>	<b>4</b>	<b>3</b>	<b>7</b>	<b>5</b>	<i>failure</i>
		<b>2</b>	<b>3</b>	<b>5</b>	<b>-7</b>	<i>failure</i>
		<b>3</b>	<b>4</b>	<b>7</b>	<b>5</b>	<i>failure</i>
		<b>3</b>	<b>2</b>	<b>5</b>	<b>-7</b>	<i>failure</i>

Use  $\Delta x_1 = \Delta x_2 = 0.5$

<b>4</b>	<i>Exploration</i>	3.5	3	6.5	1.25	<i>failure</i>
		2.5	3	5.5	-4.75	<i>failure</i>
		3	3.5	6.5	1.25	<i>failure</i>
		3	2.5	5.5	-4.75	<i>failure</i>

Use  $\Delta x_1 = \Delta x_2 = 0.25$

<i>5</i>	<i>Exploration</i>	<i>3.25</i>	<i>3</i>	<i>6.25</i>	<i>-0.4375</i>	<i>Success</i>
		<i>3.25</i>	<i>3.25</i>	<i>6.5</i>	<i>1.125</i>	<i>failure</i>
		<i>3.25</i>	<i>2.75</i>	<i>6</i>	<i>-1.875</i>	<i>failure</i>

### **Base 3 ( 3.25 , 3 ) , Set 2 ( 2 , 2 )**

<b>6</b>	<i>Pattern move</i>	4.5	4	8.5	16.25	<i>failure</i>
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Use  $\Delta x_1 = \Delta x_2 \equiv 0.125$

<b>7</b>	<i>Exploration</i>	<b>3.375</b>	<b>3</b>	<b>6.375</b>	<b>0.391</b>	<i>failure</i>
		<b>3.125</b>	<b>3</b>	<b>6.125</b>	<b>-1.234</b>	<i>failure</i>
		<b>3.25</b>	<b>3.125</b>	<b>6.375</b>	<b>0.328</b>	<i>failure</i>
		<b>3.25</b>	<b>2.875</b>	<b>6.125</b>	<b>-1.172</b>	<i>failure</i>

Use  $\Delta x_1 = \Delta x_2 = 0.0625$

<b>8</b>	<b><i>Exploration</i></b>	<b>3.3125</b>	<b>3</b>	<b>6.3125</b>	<b>-0.027</b>	<b><i>Success</i></b>
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