



INDIAN INSTITUTE OF SCIENCE

Water Resources Systems: **Modeling Techniques and Analysis**

Lecture - 5

Course Instructor : Prof. P. P. MUJUMDAR

Department of Civil Engg., IISc.

Summary of the previous lecture

- Optimization of a function of a single variable

necessary condition $f'(x) = 0$

Sufficiency condition $f''(x)|_{x_0} < 0$ $f''(x)|_{x_0} > 0$

Function of multiple variables

necessary condition $\frac{\partial f}{\partial x_1} = \frac{\partial f}{\partial x_2} = \dots = \frac{\partial f}{\partial x_n} = 0$

Sufficiency condition:

Hessian matrix $H[f(X)] = \begin{bmatrix} \frac{\partial^2 f(X)}{\partial x_1^2} & \frac{\partial^2 f(X)}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f(X)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(X)}{\partial x_2^2} \end{bmatrix}$

- H positive definite at $X = X_0$... Minimum
- H negative definite at $X = X_0$ Maximum

Example – 1

Examine the function for convexity/concavity and determine the values at extreme points

$$f(X) = -x_1^2 - x_2^2 - 4x_1 - 8$$

The stationary point is obtained by solving

$$\frac{\partial f}{\partial x_1} = -2x_1 - 4 = 0 \quad \text{and} \quad \frac{\partial f}{\partial x_2} = -2x_2 = 0$$

$$x_1 = -2, x_2 = 0$$

$$X = (-2, 0)$$

Example – 1 (Contd.)

- Hessian matrix is

$$H[f(X)] = \begin{bmatrix} \frac{\partial^2 f(X)}{\partial x_1^2} & \frac{\partial^2 f(X)}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f(X)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(X)}{\partial x_2^2} \end{bmatrix}_{(-2,0)}$$

Hessian matrix evaluated at stationary point (-2,0)

Example – 1 (Contd.)

$$f(X) = -x_1^2 - x_2^2 - 4x_1 - 8$$

$$\frac{\partial f}{\partial x_1} = -2x_1 - 4$$

$$\frac{\partial^2 f}{\partial x_1 \partial x_2} = 0$$

$$\begin{bmatrix} \frac{\partial^2 f(X)}{\partial x_1^2} & \frac{\partial^2 f(X)}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f(X)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(X)}{\partial x_2^2} \end{bmatrix}$$

$$\frac{\partial^2 f}{\partial x_1^2} = -2$$

$$\frac{\partial f}{\partial x_2} = -2x_2$$

$$\frac{\partial^2 f}{\partial x_2 \partial x_1} = 0$$

$$\frac{\partial^2 f}{\partial x_2^2} = -2$$

Example – 1 (Contd.)

Hessian matrix is

$$H[f(X)] = \begin{bmatrix} -2 & 0 \\ 0 & -2 \end{bmatrix}$$

Eigen values of Hessian matrix:

$$|\lambda I - H[f(X)]| = 0$$

$$|\lambda I - H| = \begin{bmatrix} \lambda + 2 & 0 \\ 0 & \lambda + 2 \end{bmatrix}$$

$$(\lambda + 2)^2 = 0$$

Eigen values are $\lambda_1 = -2, \lambda_2 = -2$

Example – 1 (Contd.)

- As both the eigen values are negative, the matrix is negative definite

Hence the function has local maximum at $X = (-2, 0)$

As the Hessian matrix does not depend on x_1 and x_2 and it is negative definite matrix, the function is strictly concave and therefore the local maximum is also the global maximum

Example – 2

Determine the extreme values of the function

$$f(X) = x_1^3 + x_2^3 - 3x_1 - 12x_2 + 20$$

The stationary point is obtained by solving

$$\frac{\partial f}{\partial x_1} = 3x_1^2 - 3 = 0 \quad x_1 = \pm 1$$

and

$$\frac{\partial f}{\partial x_2} = 3x_2^2 - 12 = 0 \quad x_2 = \pm 2$$

Four solutions

$$X = (-1, -2), (1, 2), (1, -2) \text{ and } (-1, 2)$$

Example – 2 (Contd.)

- Hessian matrix is

$$H[f(X)] = \begin{bmatrix} \frac{\partial^2 f(X)}{\partial x_1^2} & \frac{\partial^2 f(X)}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f(X)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(X)}{\partial x_2^2} \end{bmatrix}$$

$$f(X) = x_1^3 + x_2^3 - 3x_1 - 12x_2 + 20$$

$$\frac{\partial f}{\partial x_1} = 3x_1^2 - 3 \qquad \frac{\partial^2 f}{\partial x_1 \partial x_2} = 0$$

$$\frac{\partial^2 f}{\partial x_1^2} = 6x_1$$

Example – 2 (Contd.)

$$f(X) = x_1^3 + x_2^3 - 3x_1 - 12x_2 + 20$$

$$\frac{\partial f}{\partial x_2} = 3x_2^2 - 12 \qquad \frac{\partial^2 f}{\partial x_2 \partial x_1} = 0$$

$$\frac{\partial^2 f}{\partial x_2^2} = 6x_2$$

Hessian matrix is

$$H[f(X)] = \begin{bmatrix} 6x_1 & 0 \\ 0 & 6x_2 \end{bmatrix}$$

Example – 2 (Contd.)

Hessian matrix is

$$H[f(X)] = \begin{bmatrix} 6x_1 & 0 \\ 0 & 6x_2 \end{bmatrix}$$

Eigen values of Hessian matrix:

$$|\lambda I - H[f(X)]| = 0$$

$$|\lambda I - H| = \begin{bmatrix} \lambda - 6x_1 & 0 \\ 0 & \lambda - 6x_2 \end{bmatrix} = 0$$

$$(\lambda - 6x_1)(\lambda - 6x_2) = 0$$

Eigen values are $\lambda_1 = 6x_1$, $\lambda_2 = 6x_2$

Example – 2 (Contd.)

Hessian matrix at

$$H[f(X)] = \begin{bmatrix} 6x_1 & 0 \\ 0 & 6x_2 \end{bmatrix}_{(1,2)}$$

Eigen values are $\lambda_1 = 6x_1$, $\lambda_2 = 6x_2$

$$\lambda_1 = 6, \lambda_2 = 12$$

All the eigen values of Hessian matrix are positive, hence the matrix is positive definite at $X = (1, 2)$

Therefore the function has a local minimum at this point

$$f_{\min}(X) = 1^3 + 2^3 - 3 \times 1 - 12 \times 2 + 20 = 2$$

Example – 2 (Contd.)

Hessian matrix at

$$H[f(X)] = \begin{bmatrix} 6x_1 & 0 \\ 0 & 6x_2 \end{bmatrix} (-1, -2)$$

Eigen values are $\lambda_1 = 6x_1, \lambda_2 = 6x_2$

$$\lambda_1 = -6, \lambda_2 = -12$$

All the eigen values of Hessian matrix are negative, hence the matrix is negative definite at $X = (-1, -2)$

Therefore the function has a local maximum at this point

$$\begin{aligned} f_{\max}(X) &= (-1)^3 + (-2)^3 - 3 \times (-1) - 12 \times (-2) + 20 \\ &= 38 \end{aligned}$$

Example – 2 (Contd.)

Hessian matrix at

$$H[f(X)] = \begin{bmatrix} 6x_1 & 0 \\ 0 & 6x_2 \end{bmatrix} (-1, 2) \text{ or } (1, -2)$$

Eigen values are -6 and 12 (or 6 and -12)

The H matrix is neither positive definite nor negative definite at these two points

Constrained Optimization

Optimization: Methods of Calculus

Constrained Optimization:

- $f(X)$ is a function of n variables represented by vector $X = (x_1, x_2, x_3, \dots, x_n)$

Maximize or Minimize $f(X)$

Subject to (s.t.) $g_j(X) \leq 0 \quad j = 1, 2, \dots, m$

$$m \leq n$$

$f(X)$ and $g(X)$ may or may not be linear functions

- If $m > n$ the problem is over defined and there will be no solution unless redundant constraints are present

Optimization: Methods of Calculus

Constrained Optimization:

- Function with equality constraints
- Function with inequality constraints

Function with equality constraints

Maximize or Minimize $f(X)$

(s.t.) $g_j(X) = 0 \quad j = 1, 2, \dots, m$

$$X = \begin{cases} x_1 \\ x_2 \\ \vdots \\ x_n \end{cases}$$

Two methods discussed

- Direct substitution
- Lagrange multipliers

Optimization: Methods of Calculus

Direct substitution:

- Reduce the problem to an unconstrained problem by expressing m variables in terms of the remaining $(n - m)$ variables.

For example,

3 variables : x_1, x_2, x_3

2 constraints

x_2, x_3 may be expressed in terms of x_1 and
render the problem as unconstrained
problem with only x_1 involved

Optimization: Methods of Calculus

Limitation:

- With higher no. of variables and constraints this method becomes quite cumbersome.
- Constraint equations are often non-linear – difficult to solve them simultaneously.

Example – 3

Minimize the function

$$f(X) = x_1^2 + x_2^2 + 4x_1x_2$$

s.t.

$$x_1 + x_2 - 4 = 0$$

Solution:

$$x_1 = 4 - x_2$$

The modified function is

$$\begin{aligned} f(X) &= (4 - x_2)^2 + x_2^2 + 4(4 - x_2)x_2 \\ &= 16 + 8x_2 - 2x_2^2 \end{aligned}$$

Example – 3 (Contd.)

$$\frac{\partial f}{\partial x_2} = 8 - 4x_2$$

$$\frac{\partial f}{\partial x_2} = 0$$

$$8 - 4x_2 = 0$$

$$x_2 = 2$$

$$\frac{\partial^2 f}{\partial x_2^2} = -4 < 0,$$

~~Global~~ *Local* maximum occurs at $x_2 = 2$

Optimization: Methods of Calculus

Lagrange multipliers:

Maximize or Minimize $f(X)$

s.t.

$$g_j(X) = 0 \quad j = 1, 2, \dots, m$$

- Introduce one additional variable corresponding to each constraint.
- Lagrange function ~~$f(X)$~~ is written as

$$\del{L = f(X) - \lambda_j g_j(X)} \quad L = f(x) - \sum_{j=1}^m \lambda_j g_j(x)$$

- When $g_j(X) = 0$, optimizing L is same as optimizing $f(X)$
- The problem is transformed to unconstrained optimization problem

Optimization: Methods of Calculus

$$L = f(X) - \lambda_1 g_1(X) - \lambda_2 g_2(X) - \dots - \lambda_m g_m(X)$$

- The problem of n variables with m constraints is changed to a single problem of $(n + m)$ variables with no constraints.

Optimization: Methods of Calculus

Necessary condition: For a function $f(X)$ subject to the constraints $g_j(X) = 0, j = 1, 2, \dots, m$ to have a relative optimum at a point X^* is that the first partial derivatives of the Lagrange function with respect to each of its arguments must be zero.

$$L = f(X) - \sum_{j=1}^m \lambda_j g_j(X)$$

$$\frac{\partial L}{\partial x_i} = 0 \quad i = 1, 2, \dots, n$$

$$\frac{\partial L}{\partial \lambda_j} = 0 \quad j = 1, 2, \dots, m$$

Optimization using Calculus

The $(n + m)$ simultaneous equations are solved to get a solution, (X^*, λ^*) .

Sufficiency condition:

The second partial derivatives are denoted by

$$L_{ij} = \frac{\partial^2 L}{\partial x_i \partial x_j} \Big|_{(X^*, \lambda^*)} \quad i = 1, 2, \dots, n$$

$$g_{ij} = \frac{\partial g_j(X)}{\partial x_i} \Big|_{X^*} \quad j = 1, 2, \dots, m$$

Optimization using Calculus

Sufficiency condition:

$$|D| = \begin{array}{c} \left. \begin{array}{c} n \\ \text{terms} \end{array} \right\} \begin{array}{c} \overbrace{\begin{array}{cccc} L_{11} - Z & L_{12} & \dots & L_{1n} \\ L_{21} & L_{22} - Z & \dots & L_{2n} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ L_{n1} & L_{n2} & \dots & L_{nn} - Z \end{array}}^{n \text{ terms}} & \overbrace{\begin{array}{cccc} g_{11} & g_{21} & \dots & g_{m1} \\ g_{12} & g_{22} & \dots & g_{m2} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ g_{1n} & g_{2n} & \dots & g_{mn} \end{array}}^{m \text{ terms}} \\ \hline \left. \begin{array}{c} m \\ \text{terms} \end{array} \right\} \begin{array}{cccc} g_{11} & g_{12} & \dots & g_{1n} \\ g_{21} & g_{22} & \dots & g_{2n} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ g_{m1} & g_{m2} & \dots & g_{mn} \end{array} \end{array} \begin{array}{cccc} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \dots & 0 \end{array}$$

$$|D| = 0$$

Optimization using Calculus

Leads to a polynomial in Z of the order $(n - m)$

Solve for Z

If all Z values are positive X^* corresponds to minimum

If all Z values are negative X^* corresponds to maximum

If some values are positive and some are negative ... X^* is neither a minimum nor a maximum.