

Optimal Design of Energy Systems

Chapter 16 Calculus Methods of Optimization

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Chapter 16. Calculus Methods of Optimization

16.1 Continued exploration of calculus methods

- Lagrange multipliers (from Chap.8)

$$\begin{array}{l} y = y(x_1, x_2, \dots, x_n) \\ \phi_1(x_1, x_2, \dots, x_n) = 0 \\ \vdots \\ \phi_m(x_1, x_2, \dots, x_n) = 0 \end{array} \quad \rightarrow \quad \begin{array}{l} \nabla y - \sum_{i=1}^m \lambda_i \nabla \phi_i = 0 \\ \phi_1(x_1, x_2, \dots, x_n) = 0 \\ \vdots \\ \phi_m(x_1, x_2, \dots, x_n) = 0 \end{array} \quad \left. \vphantom{\begin{array}{l} \nabla y - \sum_{i=1}^m \lambda_i \nabla \phi_i = 0 \\ \phi_1(x_1, x_2, \dots, x_n) = 0 \\ \vdots \\ \phi_m(x_1, x_2, \dots, x_n) = 0 \end{array}} \right\} \begin{array}{l} n+m \text{ scalar} \\ \text{equations} \end{array}$$



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16.2 The nature of the gradient vector (∇y)

1. normal to the surface of constant y

For arbitrary vector : $dx_1\hat{i}_1 + dx_2\hat{i}_2 + dx_3\hat{i}_3$

To be tangent to the surface : $dy = \frac{\partial y}{\partial x_1}dx_1 + \frac{\partial y}{\partial x_2}dx_2 + \frac{\partial y}{\partial x_3}dx_3 = 0$

$$\rightarrow dx_1 = -\frac{(\partial y / \partial x_2)dx_2 + (\partial y / \partial x_3)dx_3}{\partial y / \partial x_1}$$

Tangent vector : $T = \left[-\frac{(\partial y / \partial x_2)dx_2 + (\partial y / \partial x_3)dx_3}{\partial y / \partial x_1} \right] \hat{i}_1 + dx_2\hat{i}_2 + dx_3\hat{i}_3$

Gradient vector : $\nabla y = \frac{\partial y}{\partial x_1}\hat{i}_1 + \frac{\partial y}{\partial x_2}\hat{i}_2 + \frac{\partial y}{\partial x_3}\hat{i}_3$

$T \cdot \nabla y = 0$ \rightarrow gradient vector is normal to all tangent vectors

\rightarrow gradient vector normal to the surface



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16.2 The nature of the gradient vector (∇y)

2. indicate direction of maximum rate of change of y with respect to x

to find maximum dy :
$$dy = \frac{\partial y}{\partial x_1} dx_1 + \frac{\partial y}{\partial x_2} dx_2 + \cdots + \frac{\partial y}{\partial x_n} dx_n$$

constraints :
$$(dx_1)^2 + (dx_2)^2 + \cdots + (dx_n)^2 = r^2$$

using Lagrange multipliers :
$$\frac{\partial y}{\partial x_i} - 2\lambda dx_i = 0 \rightarrow dx_i = \frac{1}{2\lambda} \frac{\partial y}{\partial x_i}$$

In vector form :

$$dx_1 \hat{i}_1 + dx_2 \hat{i}_2 + \cdots + dx_n \hat{i}_n \rightarrow \frac{1}{2\lambda} \left[\frac{\partial y}{\partial x_1} \hat{i}_1 + \frac{\partial y}{\partial x_2} \hat{i}_2 + \cdots + \frac{\partial y}{\partial x_n} \hat{i}_n \right] = \frac{1}{2\lambda} \nabla y$$

$\rightarrow \nabla y$ indicates the direction of maximum change for a given distance in the space



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16.2 The nature of the gradient vector (∇y)

3. points in the direction of increasing y

small move in the x_1 - x_2 space : $dy = \frac{\partial y}{\partial x_1} dx_1 + \frac{\partial y}{\partial x_2} dx_2$

If the move is made in the direction of ∇y :

$$\frac{dx_i}{\partial y / \partial x_i} = c \rightarrow dx_1 = c(\partial y / \partial x_1), \quad dx_2 = c(\partial y / \partial x_2)$$

$$dy = c \left[\left(\frac{\partial y}{\partial x_1} \right)^2 + \left(\frac{\partial y}{\partial x_2} \right)^2 \right] \geq 0$$

→ dy is equal or greater than zero

→ y always increase in the direction of ∇y



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16.5 Two variables and one constraint (prove Lagrange multiplier method)

Optimize $y(x_1, x_2)$ subject to $\phi(x_1, x_2) = 0$

Taylor expansion : $\Delta y \approx \left(\frac{\partial y}{\partial x_1} \right) \Delta x_1 + \left(\frac{\partial y}{\partial x_2} \right) \Delta x_2$

$$d\phi = \left(\frac{\partial \phi}{\partial x_1} \right) \Delta x_1 + \left(\frac{\partial \phi}{\partial x_2} \right) \Delta x_2 = 0 \rightarrow \Delta x_1 = - \frac{\partial \phi / \partial x_2}{\partial \phi / \partial x_1} \Delta x_2$$

$$\Delta y = \left[- \frac{\partial y}{\partial x_1} \frac{\partial \phi / \partial x_2}{\partial \phi / \partial x_1} + \frac{\partial y}{\partial x_2} \right] \Delta x_2 \stackrel{=0}{=} \quad \text{Let } \lambda = \frac{\partial y / \partial x_1}{\partial \phi / \partial x_1}$$

$$\frac{\partial y}{\partial x_2} - \lambda \frac{\partial \phi}{\partial x_2} = 0$$

$$\frac{\partial y}{\partial x_1} - \lambda \frac{\partial \phi}{\partial x_1} = 0$$



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16.8 Alternate expression of constrained optimization problem

optimize $y(x_1, x_2)$

subject to $\phi(x_1, x_2) = b$

unconstrained function $L(x_1, x_2) = y(x_1, x_2) - \lambda[\phi(x_1, x_2) - b]$

optimum occurs where $\nabla L = 0$

$$\left. \begin{aligned} \frac{\partial L}{\partial x_1} &= \frac{\partial y}{\partial x_1} - \lambda \frac{\partial \phi}{\partial x_1} = 0 \\ \frac{\partial L}{\partial x_2} &= \frac{\partial y}{\partial x_2} - \lambda \frac{\partial \phi}{\partial x_2} = 0 \\ \phi(x_1, x_2) - b &= 0 \end{aligned} \right\} \text{find optimum point}$$



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16.9 Interpretation λ of as the sensitivity coefficient

sensitivity coefficient (SC) :

$$y(x_1, x_2) \rightarrow SC = \frac{\partial y^*}{\partial b} = \frac{\partial y^*}{\partial x_1} \frac{\partial x_1}{\partial b} + \frac{\partial y^*}{\partial x_2} \frac{\partial x_2}{\partial b} \dots (1)$$

$$\phi(x_1, x_2) = b \rightarrow \frac{\partial \phi}{\partial b} = \frac{\partial \phi}{\partial x_1} \frac{\partial x_1}{\partial b} + \frac{\partial \phi}{\partial x_2} \frac{\partial x_2}{\partial b} - 1 = 0 \dots (2)$$

$$\lambda = \frac{(\partial y^* / \partial x_1^*)}{(\partial \phi / \partial x_1^*)} = \frac{(\partial y^* / \partial x_2^*)}{(\partial \phi / \partial x_2^*)}$$

$$(2) \times \lambda \rightarrow \frac{\partial y}{\partial x_1} \frac{\partial x_1}{\partial b} + \frac{\partial y}{\partial x_2} \frac{\partial x_2}{\partial b} - \lambda = 0$$

$$(1) \rightarrow SC = \lambda$$

