The L-Shaped Method

Operations Research

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Contents

- The L-Shaped Method
- Example: Capacity Expansion Planning
- Examples with Optimality Cuts [§5.1a of BL]
- Examples with Feasibility Cuts [§5.1b of BL]

Table of Contents

- 1 The L-Shaped Method
- Example: Capacity Expansion Planning
- 3 Examples with Optimality Cuts [§5.1a of BL]
- Examples with Feasibility Cuts [§5.1b of BL]

Extensive Form

Stochastic linear program in **extensive form**:

(EF):
$$\min c^T x + \mathbb{E}_{\omega}[\min q(\omega)^T y(\omega)]$$

$$Ax = b$$

$$T(\omega)x + W(\omega)y(\omega) = h(\omega)$$

$$x \ge 0, y(\omega) \ge 0$$

- First-stage decisions: $x \in \mathbb{R}^{n_1}$
- second-stage decisions: $y(\omega) \in \mathbb{R}^{n_2}$
- First-stage parameters: $c \in \mathbb{R}^{n_1}$, $b \in \mathbb{R}^{m_1}$, $A \in \mathbb{R}^{m_1 \times n_1}$
- Second-stage parameters: $q(\omega) \in \mathbb{R}^{n_2}$, $h(\omega) \in \mathbb{R}^{m_2}$, $T(\omega) \in \mathbb{R}^{m_2 \times n_1}$ and $W(\omega) \in \mathbb{R}^{m_2 \times n_2}$



Value Function

Second-stage value function:

$$(S_{\omega}): \quad Q_{\omega}(x) = \min_{y} q_{\omega}^{T} y$$
 $W_{\omega} y = h_{\omega} - T_{\omega} x$
 $y \geq 0.$

Interpretation: cost of best possible reaction to x and ω

Expected value function:

$$V(x) = \sum_{\omega=1}^{N} p_{\omega} Q_{\omega}(x).$$

Interpretation: cost of best possible reaction to ${\it x}$ before knowing ω



Complete Recourse

Define

- $K_1 = \{x : Ax = b, x \ge 0\}$
- $K_2(\omega) = \{x : \exists y, T_\omega x + W_\omega y = h_\omega, y \ge 0\}$
- $K_2 = \text{dom } V$

Interpretation of K_1 , $K_2(\omega)$, K_2 ?

Relative complete recourse: obeying first-stage constraints ensures feasible second-stage decisions exist:

pos
$$W = \mathbb{R}^{m_2}$$

Complete recourse: feasible second-stage decision exists, regardless of first-stage decision and realization of uncertainty:

$$K_2 = \mathbb{R}^{n_1}$$



Properties of Value Functions

Dual of (S_{ω}) :

$$(D_{\omega}): \max_{\pi} \pi^{T}(h_{\omega} - T_{\omega}x) \ \pi^{T}W_{\omega} \leq q_{\omega}^{T}$$

Denote $\pi_{\omega 0}$ as dual optimal multipliers of (S_{ω}) given x_0 :

- **1** V(x) and $Q_{\omega}(x)$ are piecewise linear convex functions of x
- ② $\pi_{\omega 0}^T(h_{\omega}-T_{\omega}x)$ is a supporting hyperplane of $Q_{\omega}(x)$ at x_0

We recall a previous result for the proof

Proof:

- \bullet \bullet \bullet has finite number of dual optimal multipliers
- ② Strong duality and $\pi_{\omega 0} \in \partial Q_{\omega}(h_{\omega} T_{\omega}x_0)$
- **③** Follows from previous bullet and $V(x) = \sum_{\omega=1}^{N} p_{\omega} Q_{\omega}(x)$

The diag operator

Consider a set of matrices A_i , i = 1, ..., n (not necessarily square)

The matrix $diag(A_1, ..., A_n)$ is defined as

$$diag(A_1, A_2, \dots, A_n) = \begin{pmatrix} A_1 & 0 & \dots & 0 \\ 0 & A_2 & \dots & 0 \\ \vdots & & & & \\ 0 & 0 & \dots & A_n \end{pmatrix}$$

Not necessarily a square matrix

$$(S): \quad \min_{y} \sum_{\omega=1}^{N} p_{\omega} q_{\omega}^{T} y_{\omega}$$

$$Wy = h - Tx$$

$$y \ge 0$$

where

•
$$y^T = [y_1^T, \dots, y_N^T]$$

•
$$h^T = [h_1^T, \dots, h_N^T]$$

•
$$T = \operatorname{diag} (T_{\omega}, \omega = 1, \dots, N)$$

•
$$W = \text{diag} (W_{\omega}, \omega = 1, \dots, N)$$

Is there a relationship between the feasible regions of the duals of (S) and (S_{ω}) ?

Supporting Hyperplanes of V

Denote

- *V*: the set of extreme vertices of $\{\pi : \pi^T W \leq q^T\}$
- V_{ω} : the set of extreme vertices of $\{\pi : \pi^T W_{\omega} \leq q_{\omega}^T \}$

Then

$$V = \{(p_1 \pi_1^T, \dots, p_N \pi_N^T)^T : \pi_1 \in V_1, \dots, \pi_N \in V_N\}$$

Domain of *V*

Denote

- *R*: the set of extreme rays of $\{\pi : \pi^T W \leq q^T\}$
- R_{ω} : the set of extreme rays of $\{\pi: \pi^T W_{\omega} \leq q_{\omega}^T\}$

Then

$$\textit{\textbf{R}} = \{(\textbf{0}, \dots, \sigma_{\omega}^{\intercal}, \dots, \textbf{0})^{\intercal} : \sigma_{\omega} \in \textit{\textbf{R}}_{\omega}, \omega = \textbf{1}, \dots, \textit{\textbf{N}}\}$$

Deterministic Equivalent Program

The original problem (EF) can be written as a **deterministic** equivalent program:

$$min c^{T}x + \theta$$

$$Ax = b$$

$$\sigma^{T}(h - Tx) \le 0, \sigma \in R$$

$$\theta \ge \pi^{T}(h - Tx), \pi \in V$$

$$x \ge 0$$

Master Problem

Define master problem as

$$(M): \quad z_k = \min c^T x + \theta$$

$$Ax = b$$

$$\sigma^T (h - Tx) \le 0, \sigma \in R_k \subseteq R$$

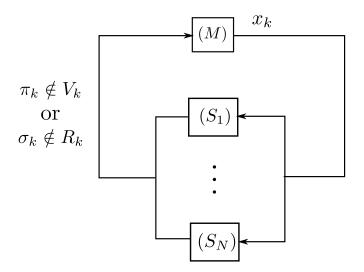
$$\theta \ge \pi^T (h - Tx), \pi \in V_k \subseteq V$$

$$x \ge 0$$

$$(1)$$

- Feasibility cuts: equation 1
- Optimality cuts: equation 2

Overall Scheme



Bounds

Solution of master provides:

- lower bound $z_k \leq z^*$
- candidate solution x_k
- under-estimator $\theta_k \leq V(x_k)$

Solution of *all* (S_{ω}) with input x_k provides

- upper bound $c^T x_k + \sum_{\omega=1}^N p_\omega q_\omega^T y_{\omega,k+1} \geq z^\star$
- new vertex $\pi_{k+1} = (p_1 \pi_{1,k+1}^T, \dots, p_N \pi_{N,k+1}^T)^T$ or new extreme ray $\sigma_{k+1} = (0, \dots, \sigma_{\omega}^T, \dots, 0)^T$

The L-Shaped Algorithm

Step 0: Set
$$k = 0$$
, $V_0 = R_0 = \emptyset$
Step 1: Solve (*M*)

- If (M) is feasible, store x_k
- If (M) is infeasible, exit: infeasible

Step 2: For
$$\omega = 1, ..., N$$
, solve (S_{ω}) with x_k as input

- If (S_{ω}) is infeasible, let $S_{k+1} = S_k \cup \{\sigma_{k+1}\}$, where σ_{k+1} is an extreme ray of (S_{ω}) , let k = k + 1 and return to step 1
- If (S_{ω}) is feasible, store $\pi_{\omega,k+1}$

Step 3: Let
$$V_{k+1} = V_k \cup \{(p_1\pi_{1,k+1}, \dots, p_N\pi_{N,k+1})\}$$

- If $V_k = V_{k+1}$ then terminate with (x_k, y_{k+1}) as the optimal solution.
- Else, let k = k + 1 and return to step 1



Table of Contents

- 1 The L-Shaped Method
- Example: Capacity Expansion Planning
- 3 Examples with Optimality Cuts [§5.1a of BL]
- 4 Examples with Feasibility Cuts [§5.1b of BL]

Example: Capacity Expansion Planning

$$\min_{x,y\geq 0} \sum_{i=1}^{n} (I_i \cdot x_i + \mathbb{E}_{\xi} \sum_{j=1}^{m} C_i \cdot T_j \cdot y_{ij}(\omega))$$
s.t.
$$\sum_{i=1}^{n} y_{ij}(\omega) = D_j(\omega), j = 1, \dots, m$$

$$\sum_{j=1}^{m} y_{ij}(\omega) \leq x_i, i = 1, \dots, n-1$$

- I_i, C_i: fixed/variable cost of technology i
- $D_j(\omega)$, T_j : height/width of load block j
- $y_{ij}(\omega)$: capacity of i allocated to j
- x_i: capacity of i

Note: D_i is not dependent on ω



Problem Data

Two possible realizations of load duration curve:

Reference scenario: 10%

• 10x wind scenario: 90%

	Duration (hours)	Level (MW)	Level (MW)	
		Reference scenario	10x wind scenario	
Base load	8760	0-7086	0-3919	
Medium load	7000	7086-9004	3919-7329	
Peak load	1500	9004-11169	7329-10315	

Slave Problem

$$(S_{\omega}): \quad \min_{y\geq 0} \sum_{i=1}^{n} \sum_{j=1}^{m} C_{i} \cdot T_{j} \cdot y_{ij}$$

$$(\lambda_{j}(\omega)): \quad \sum_{i=1}^{n} y_{ij} = D_{j}(\omega), j = 1, \dots, m$$

$$(\rho_{i}(\omega)): \quad \sum_{i=1}^{m} y_{ij} \leq \bar{x}_{i}, i = 1, \dots, n-1$$

where \bar{x} has been fixed from the master problem

Sequence of Investment Decisions

Iteration	Coal (MW)	Gas (MW)	Nuclear (MW)	Oil (MW)
1	0	0	0	0
2	0	0	0	8736
3	0	0	0	15999.6
4	0	14675.5	0	0
5	10673.8	0	0	0
6	10673.8	0	0	13331.8
7	0	163.8	7174.5	3830.8
8	0	3300.6	7868.4	0
9	0	5143.4	7303.9	1679.4
10	3123.9	1948.1	4953.7	1143.3
11	1680	4322.4	6625	0
12	8747.6	1652.8	0	768.6
13	5701.9	464.9	4233.6	768.6
14	4935.9	1405	3994.7	0
15	6552.6	386.3	3173.7	882.9
16	5085	1311	3919	854

Observations

- Investment candidate in each iteration necessarily different from all past iterations
- 'Greedy' behavior: low capital cost in early iterations

Table of Contents

- 1 The L-Shaped Method
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- 4 Examples with Feasibility Cuts [§5.1b of BL]

Example 1

$$z = \min 100x_1 + 150x_2 + \mathbb{E}_{\xi}(q_1y_1 + q_2y_2)$$

s.t. $x_1 + x_2 \le 120$
 $6y_1 + 10y_2 \le 60x_1$
 $8y_1 + 5y_2 \le 80x_2$
 $y_1 \le d_1, y_2 \le d_2$
 $x_1 \ge 40, x_2 \ge 20, y_1, y_2 \ge 0$

$$\xi = (d_1, d_2, q_1, q_2) = \begin{cases} (500, 100, -24, -28), & p_1 = 0.4 \\ (300, 300, -28, -32), & p_2 = 0.6 \end{cases}$$



- Step 1. $\min\{100x_1 + 150x_2 | x_1 + x_2 < 120, x_1 > 40, x_2 > 20\}$
- $x^1 = (40, 20)^T$, $\theta^1 = -\infty$
- Step 3. For $\xi = \xi_1$ solve

$$\min\{-24y_1 - 28y_2 | 6y_1 + 10y_2 \le 2400, 8y_1 + 5y_2 \le 1600$$

$$0 \le y_1 \le 500, 0 \le y_2 \le 100\}$$

$$w_1 = -6100, v^T = (137.5, 100), \pi_1^T = (0, -3, 0, -13)$$

For
$$\xi = \xi_2$$
 solve

$$\min\{-28y_1 - 32y_2|6y_1 + 10y_2 \le 2400, 8y_1 + 5y_2 \le 1600$$
$$0 \le y_1 \le 300, 0 \le y_2 \le 300\}$$

$$w_2 = -8384, y^T = (80, 192), \pi_2^T = (-2.32, -1.76, 0, 0)$$

Iteration 1: Optimality Cut

$$h_1 = (0, 0, 500, 100)^T, h_2 = (0, 0, 300, 300)^T$$

 $T_{\cdot,1} = (-60, 0, 0, 0)^T, T_{\cdot,2} = (0, -80, 0, 0)^T$

- $e_1 = 0.4 \cdot \pi_1^T \cdot h_1 + 0.6 \cdot \pi_2^T \cdot h_2 = 0.4 \cdot (-1300) + 0.6 \cdot (0) = -520$
- $E_1 = 0.4 \cdot \pi_1^T T + 0.6 \cdot \pi_2^T T = 0.4(0, 240) + 0.6(139.2, 140.8) = (83.52, 180.48)$
- $w^1 = -520 (83.52, 180.48) \cdot x^1 = -7470.4$
- $w^1 = -7470.4 > \theta^1 = -\infty$, therefore add the cut $83.52x_1 + 180.48x_2 + \theta \ge -520$

Step 1. Solve master

$$\begin{aligned} &\min\{100x_1 + 150x_2 + \theta | x_1 + x_2 \le 120, x_1 \ge 40, x_2 \ge 20, \\ &83.52x_1 + 180.48x_2 + \theta \ge -520\} \\ &z = -2299.2, x^2 = (40, 80)^T, \theta^2 = -18299.2 \end{aligned}$$

• *Step 3.* Add the cut $211.2x_1 + \theta \ge -1584$

• Step 1. Solve master.

$$z = -1039.375, x^3 = (66.828, 53.172)^T, \theta^3 = -15697.994$$

• Step 3. Add the cut $115.2x_1 + 96x_2 + \theta \ge -2104$



• Step 1. Solve master.

$$z = -889.5, x^4 = (40, 33.75)^T, \theta^4 = -9952$$

• Step 3. There are multiple solutions for $\xi = \xi_2$. Select one, add the cut 133.44 $x_1 + 130.56x_2 + \theta \ge 0$

Step 1. Solve master

$$\begin{aligned} & \min\{100x_1+150x_2+\theta|x_1+x_2\leq 120, x_1\geq 40, x_2\geq 20,\\ & 83.52x_1+180.48x_2+\theta\geq -520, 211.2x_1+\theta\geq -1584\\ & 115.2x_1+96x_2+\theta\geq -2104, 133.44x_1+130.56x_2+\theta\geq 0\}\\ & z=-855.833, x^5=(46.667, 36.25)^T, \theta^5=-10960 \end{aligned}$$

• Step 3. $w_5 = -520 - (83.52, 180.48) \cdot x^5 = -10960 = \theta^5$, stop. $x = (46.667, 36.25)^T$ is the optimal solution.

Example 2

$$z = \min \mathbb{E}_{\xi}(y_1 + y_2)$$

s.t. $0 \le x \le 10$
 $y_1 - y_2 = \xi - x$
 $y_1, y_2 \ge 0$

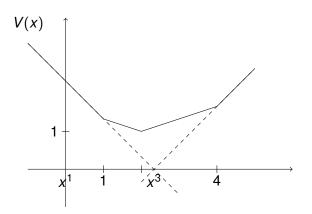
$$\xi = \begin{cases} 1 & p_1 = 1/3 \\ 2 & p_2 = 1/3 \\ 4 & p_3 = 1/3 \end{cases}$$



L-Shaped Method in Example 2

- Iteration 1, Step 1: $x^1 = 0$
- Iteration 1, Step 3: x^1 not optimal, add cut: $\theta \ge 7/3 x$
- Iteration 2, Step 1: $x^2 = 10$
- Iteration 2, Step 3: x^2 not optimal, add cut: $\theta \ge x 7/3$
- Iteration 3, Step 1: $x^3 = 7/3$
- Iteration 3, Step 3: x^3 not optimal, add cut: $\theta \ge (x+1)/3$
- Iteration 4, Step 1: $x^4 = 1.5$
- Iteration 4, Step 3: x^4 not optimal, add cut: $\theta \ge (5-x)/3$
- Iteration 3, Step 1: $x^5 = 2$
- Iteration 3, Step 3: x^5 is optimal





- $V(x^1) = 7/3$ and V(x) = 7/3 x 'around' x^1
- (7-x)/3 is the optimality cut at x^1

Table of Contents

- 1 The L-Shaped Method
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Feasibility Cuts

Consider the following problem:

(F):
$$\min w' = e^T v^+ + e^T v^-$$

s.t. $Wy + Iv^+ - Iv^- = h_k - T_k x^v$
 $y \ge 0, v^+ \ge 0, v^- \ge 0$

with dual multipliers σ^{ν} . Define

$$D_{r+1} = (\sigma^{v})^{T} T_{k}$$

$$d_{r+1} = (\sigma^{v})^{T} h_{k}$$

Step 2 of L-shaped method: For k = 1, ..., K solve (F).

- If w' = 0 for all k, go to Step 3.
- Else, add $D_{r+1}x \ge d_{r+1}$, set r = r + 1 and go to Step 1.

Example

$$\begin{aligned} &\min 3x_1 + 2x_2 - \mathbb{E}_{\xi}(15y_1 + 12y_2) \\ &\text{s.t. } 3y_1 + 2y_2 \le x_1, 2y_1 + 5y_2 \le x_2 \\ &0.8\xi_1 \le y_1 \le \xi_1, 0.8\xi_2 \le y_2 \le \xi_2 \\ &x, y \ge 0 \end{aligned}$$

$$\xi = \begin{cases} (4,4), p_1 = 0.25 \\ (4,8), p_2 = 0.25 \\ (6,4), p_3 = 0.25 \\ (6,8), p_4 = 0.25 \end{cases}$$

Generating a Feasibility Cut

For $x^1 = (0,0)^T$, $\xi = (6,8)^T$, solve

$$\min_{v^+,v^-,y} v_1^+ + v_1^- + v_2^+ + v_2^- + v_3^+ + v_3^- + \\ v_4^+ + v_4^- + v_5^+ + v_5^- + v_6^+ + v_6^- \\ \mathrm{s.t.} \ v_1^+ - v_1^- + 3y_1 + 2y_2 \leq 0, v_2^+ - v_2^- + 2y_1 + 5y_2 \leq 0 \\ v_3^+ - v_3^- + y_1 \geq 4.8, v_4^+ - v_4^- + y_2 \geq 6.4 \\ v_5^+ - v_5^- + y_1 \leq 6, v_6^+ - v_6^- + y_2 \leq 8 \\ \mathrm{We} \ \mathrm{get} \ w' = 11.2, \ \sigma^1 = (-3/11, -1/11, 1, 1, 0, 0) \\ h = (0, 0, 4.8, 6.4, 6, 8)^T, \ T_{-1} = (-1, 0, 0, 0, 0, 0)^T,$$

$$T_{.,2} = (0, -1, 0, 0, 0, 0)^T$$

 $D_1 = (-3/11, -1/11, 1, 1, 0, 0) \cdot T = (3/11, 1/11),$
 $d_1 = (-3/11, -1/11, 1, 1, 0, 0) \cdot h = 11.2$

 $3/11x_1 + 1/11x_2 \ge 11.2$



Induced Constraints

Going by the book:

- Iteration 2 master problem: $x^2 = (41.067, 0)^T$
- Iteration 2 feasibility cut: $x_2 \ge 22.4$
- Iteration 3 master problem: $x^3 = (33.6, 22.4)^T$
- Iteration 3 feasibility cut: x₂ ≥ 41.6
- Iteration 4 master problem: $x^4 = (27.2, 41.6)^T$ is feasible

Induced Constraints:

- Observe that for $\xi = (6,8)^T$, $y_1 \ge 4.8$, $y_2 \ge 6.4$
- This implies $x_1 \ge 27.2$, $x_2 \ge 41.6$, which should be added directly to the master

Personal experience: feasibility cuts are impractical

