

V:3

$$\text{Objective function} = \max_{\lambda, \mu \geq 0} \left(\min_{x, z, Y} \left[\sum_i \sum_m^i (H \alpha_i) Y_i + \sum_j \sum_d^j (H \beta_j) Y_j \right. \right. \\ \left. \left. + \sum_{ij} \left(V_m^i + \frac{3}{2000} \cdot d_{ij}^{\text{MD}} (H \gamma_{ij}) \right) X_{ij} + \sum_{jc} \theta_{jc} \left(p_j^j + 9.75 + 13.5 \cdot \frac{d_{jc}^{\text{JC}}}{500} \right) (H \delta_j) \right. \right. \\ \left. \left. + \sum_{ij} \lambda (x_{ij} - u_{ij} Y_i) + \sum_{jc} \mu_{jc} (z_{jc} - v_{jc} Y_j) \right] \right)$$

or Duality and Dual Simplex Algorithm.

$$\text{Primal} = \min_{x, Y, z} f(x, z, Y) \quad \text{s.t. } g_{ij}(x, Y) = x_{ij} - u_{ij} Y_i \leq 0 \\ h_{ij}(Y, z) = z_{jc} - v_{jc} Y_j \leq 0$$

$$\text{Lagrange function} = L(x, z, Y; \lambda, \mu) = f(x, z, Y) + \sum_{ij} \lambda_{ij} (x_{ij} - u_{ij} Y_i) \\ + \sum_{jc} \mu_{jc} (z_{jc} - v_{jc} Y_j) \quad \forall \lambda, \mu \geq 0$$

$$\text{Dual} = G(\lambda, \mu) = \min_{x, z, Y} L(x, z, Y; \lambda, \mu)$$

$$\text{Dual problem} = \max_{\lambda, \mu \geq 0} G(\lambda, \mu)$$

$V_{ij} \in I$ for all 6 Candidates

$V_{cc} \in C$ for all 30 Customer regions

Variable = Y_i, Y_j Binary

$X_{ij} \geq 0$ inflow variable from $MTG \rightarrow DC$, 瓶/年

$Z_{jc} \geq 0$ Outflow Variable from $DC \rightarrow C$, 瓶/年

transportation = $f_m^I, f_d^J, v_m^I, d_{ij}^{MD}, d_{jc}^{DC}$ p 为处理费.

Sensitivity / Robustness parameters = $\alpha_i, \beta_j, \gamma_{ij}, \delta_{jc}$ (inflation)

Tight Upper bound: $U_{ij} > 0$ is upper bound for X_{ij} (ex. 30 customers)

$V_{jc} = D_c$ is a upper bound of Z_{jc}

Multiplier: $\lambda_{ij} \geq 0, \mu_{jc} \geq 0$ a Outer layer dual parameters (shadow).

Constraints

1. Demand Satisfaction.

$$\sum_{j \in I} z_{jc} = v_c, \quad \forall c \in C$$

2. flow Balance

$$\sum_{c \in C} z_{jc} = \sum_{c \in C} x_{ij}, \quad \forall j \in I$$

3. Variable domains and integrality

$$x_{ij} \geq 0, z_{jc} \geq 0, \quad \forall i, j \in I, c \in C$$

x_{ij} is the annual flows in bottles shipped from MFG to DC

z_{jc} is the annual flow from DC to c , $\forall c \in C$

Continuous Variable must be non-negative, location binary var are binary.

4. Discrete shipment rule

$$O_{jc} \in \mathbb{Z}_+, O_{jc} \geq \frac{Z_{jc}}{6}.$$

O_{jc} , the numbers of orders shipped from D_c to $c \in C$.
Since given the information that 6 bottles per order, the total number of bottles delivered have to be $6 \cdot O_{jc}$

5. Notes regarding Big-M Constraints (Linking Variable).

$$\text{Big-M Linking Constraints in V-1: } x_{ij} \leq u_{ij} y_i, z_{jc} \leq v_{jc} y_j \\ \forall u_{ij}, z_{jc} \in M$$

In this version, I introduced Lagrange relaxation, the constraints are softened. It's no longer being considered as hard constraints in inner problem. We multiply λ_{ij}, μ_{jc} as stated below

$$\max_{\lambda, \mu \geq 0} \sum_{ij} \lambda_{ij} (x_{ij} - u_{ij} y_i) + \sum_{jc} \mu_{jc} (z_{jc} - v_{jc} y_j)$$

the max $\lambda, \mu \geq 0$ penalizes any violation of these constraints making inner problem (min) easier to solve. with fewer constraints separable structure

A rough draft of objective function:

Variable: stated in the earlier pages

Constraints: take Constraints 1-3 as Hard constraints

denote u . take linking constraints in Lagrange to be relaxed

denote L .

If: the following consists several parts,

Firstly, define the Lagrange and dual function.

$$L(x, z, Y; \lambda, \mu) =$$

$$\sum_{i=1}^n \sum_m (H_{21})_{ij} Y_{ij} + \sum_{j=1}^n \sum_i (d_{1H})_{ij} Y_{ij} + \sum_{i,j} (V_m + \frac{3}{2000} d_{ij}^{md} (H_{1ij})) x_{ij} + \sum_{jc} \frac{z_{jc}}{6} (p^j + 9.75 \\ + 3.5 \frac{d_{jc}^{pc}}{f_{50}}) (H_{fjc}) + \sum_{ij} \lambda_{ij} (x_{ij} - u_{ij} Y_{ij}) + \sum_{jc} \mu_{jc} (z_{jc} - v_{jc} Y_j)$$

denote L

$$\text{Dual (Lagrange) function: } g(\lambda, \mu) = \inf_{x, z, Y, s.t. H} L \quad \forall \lambda, \mu \geq 0$$

denote g

$$\text{Dual problem: } \max_{\lambda \geq 0, \mu \geq 0} g(\lambda, \mu) \quad \text{denote } D.$$

Secondly, the weak duality (general) situation.

Assume $(\bar{x}, \bar{z}, \bar{y})$ is feasible for both H and L_P .

$$\begin{aligned} \text{then } L(\bar{x}, \bar{z}, \bar{y}; \lambda, \mu) &= \text{Cost}(\bar{x}, \bar{z}, \bar{y}) + \sum_{ij} \lambda_{ij} (\bar{x}_{ij} - u_{ij} \bar{y}_i) \\ &\quad + \sum_{j,c} \mu_{jc} (\bar{z}_{jc} - v_{jc} \bar{y}_j) \\ &\leq \text{Cost}(\bar{x}, \bar{z}, \bar{y}) \end{aligned}$$

Since $\forall \lambda, \mu \geq 0$, then

$$g(\lambda, \mu) \leq L(\bar{x}, \bar{z}, \bar{y}; \lambda, \mu) \leq \text{Cost}(\bar{x}, \bar{z}, \bar{y})$$

taking the optimal value $p^* = \min \{ \text{Cost}(\bar{x}, \bar{z}, \bar{y}) : H, L_P \}$

$$\text{then } g(\lambda, \mu) \leq p^* = \min_{H, L_P} \text{Cost} \quad \forall \lambda, \mu \geq 0$$

$$\rightarrow \max g(\lambda, \mu) \leq p^* \quad \text{weak duality}$$

Thirdly, strong duality and complementary slackness

\rightarrow Linear programming relaxation.

If $y_i, y_j \in [0, 1]$ and the feasible region satisfies the

Slater Condition, then the problem is convex and strong duality

$$\min_{H, L_P} \text{Cost} = \max_{\lambda, \mu \geq 0} g(\lambda, \mu) = L(x^*, z^*, y^*; \lambda^*, \mu^*)$$

As well as with the complementary-slackness conditions

$$\lambda_{ij}^*(x_{ij}^* - u_{ij} y_i^*) = 0, \quad \mu_{jc}^*(z_{jc}^* - u_{jc} y_j^*) = 0.$$

denote as

Hence, the saddle point $(x^*, z^*, y^*; \lambda^*, \mu^*)$ satisfy both primal and dual optimality

Further, structure of inner min function (λ, μ fixed)

Start with defining the terms in L

$$L = \underbrace{\sum_i (f_m^i(H\alpha_i) - \sum_j \lambda_{ij} u_{ij} |Y_i)}_{\phi_i(\lambda)} + \underbrace{\sum_j (f_d^j(H\beta_j) - \sum_c \mu_{jc} v_{jc} |Y_j)}_{\psi_j(\mu)}$$

$$+ \underbrace{\sum_{ij} (v_m^i + \frac{3}{2000} d_{ij}^{mp}(H\uparrow_{ij}) + \lambda_{ij} |x_{ij})}_{\tilde{c}_{ij}^x(\lambda)}$$

$$+ \underbrace{\sum_{jc} (\frac{1}{6}(\bar{p} + 9.75 + 3.5 \frac{d_{jc}^{pc}}{500})(H\delta_{jc}) + \mu_{jc} |z_{jc})}_{\tilde{c}_{jc}^z(\mu)} \quad \text{denote } \psi_j$$

$$L = \min_v \sum_i \phi_i(\lambda) Y_i + \sum_j \psi_j(\mu) Y_j + \sum_{ij} \tilde{c}_{ij}^x(\lambda) x_{ij} + \sum_{jc} \tilde{c}_{jc}^z(\mu) z_{jc}$$

denote inn.

WTS Δ : Each x, z, Y appears independent in H

then. $Y_i^*(\lambda) = \arg \min_{y \in \{0, 1\}} \phi_i(\lambda, y) \quad y = \begin{cases} 1 & \phi_i(\lambda) < 0 \\ 0 & \phi_i(\lambda) > 0 \\ \text{either } 0/1 & \phi_i(\lambda) = 0 \end{cases}$

implying $Y_i^*(\lambda) = 1 \{ \sum_j \lambda_{ij} u_{ij} > f_m^i(H, x_i) \}$

denote Y rule for MFG

works same for Y rule for DC as following

$$Y_j^*(\mu) = 1 \{ \sum_c \mu_{jc} v_{jc} > f_d^j(H, \beta_j) \}$$

means: $Y_j^* = 1$ when $\xrightarrow{\text{satisfied}}$

B). Inner minimization over x, z

$$\min \sum_{ij} c_{ij}^x(\lambda) x_{ij} + \sum_{jc} c_{jc}^z(\mu) z_{jc} \quad \text{denote flow.}$$

This is a minimum-cost flow subproblem.

optimal flows occurs on arcs with minimal reduced cost.

In the fifth step; the subgradient of the dual function.

If (x^*, z^*, y^*) is optimal for fixed (λ, μ)

then the subgradient of the dual function is:

$$\partial_{\lambda_{ij}} g(\lambda, \mu) \ni x_{ij}^* - u_{ij} y_i^*,$$

$$\partial_{\mu_{jc}} g(\lambda, \mu) \ni x_{jc}^* - v_{jc} y_j^*$$

then, the dual ascent update or primal-dual iteration is

$$\lambda_{ij}^{k+1} = [\lambda_{ij}^k + \gamma_k (x_{ij}^k - u_{ij} y_i^k)]_+$$

$$\mu_{jc}^{k+1} = [\mu_{jc}^k + \gamma_k (x_{jc}^k - v_{jc} y_j^k)]_+$$

with the step size $\gamma_k > 0$, for convex problems, $g(\lambda^k, \mu^k)$ is monotonically non decreasing and converges to dual optimum as $k \rightarrow \infty$.

then the problem satisfied the KKT condition if:
 if Y is relaxed to $[0,1]$ the primal is

$$\min \text{Cost}(X, Z, Y) \text{ s.t. } H, U$$

also it's strong duality. A pair $(x^*, z^*, Y^*; \lambda^*, \mu^*)$
 is the optimal for V solutions if

1. primal feasibility: all H, U holds

2. Dual feasibility: $\lambda^*, \mu^* \geq 0$

3. Complementary slackness:

$$\lambda^* (x_{ij}^* - u_{ij} Y_{ij}^*) = 0, \quad \mu_{jc}^* (x_{jc}^* - v_{jc} Y_{jc}^*) = 0 \quad \text{CS}$$

4. Stationary: the gradient of Lagrangian

w.r.t cost variables vanishes which is equivalent to
 reduced cost optimality in our case

then we are free to get the optimal solutions \square

My framework / workflow:

Farkas lemma \rightarrow weak duality \rightarrow strong duality \rightarrow KKT condition \rightarrow primal-dual
 Convergence