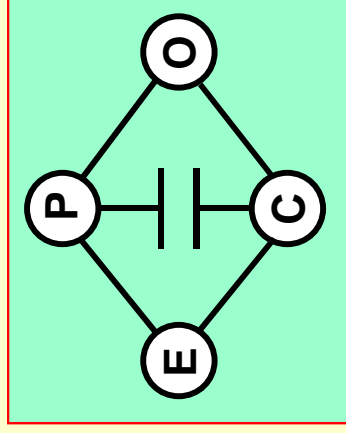


# Recent developments in modelling using supply functions

Dr Andy Philpott (EPOC)



# Summary

- Supply functions
- Price-taking optimization models
- Market distribution functions
- Unit commitment
- Nash equilibria
- Dynamic and repeated games

# Supply functions

- Offer stacks =  $\{(q,p) \text{ pairs}\}$
- Expresses  $p(q)$
- Sometimes easier to work analytically with smooth functions rather than step functions
- Supply function =  $q(p)$   
(parametrically) =  $\{(q(t),p(t) \mid t \in [0,T])\}$

# SOL BidQuery

- Mentioned in last year's workshop
- Available in Beta-test form
- Free (for the moment)

# Price-taking optimization models

- Offer short-run marginal cost of dispatch
- What is
  - SRMC function for a reservoir?
  - SRMC function for a block dispatched river chain?
  - SRMC function for a thermal unit with startup costs, shut-down costs and ramp rates?

# SRMC function for a reservoir

## Opportunity cost of stored water

- Equals water value of SPECTRA, SDDP when all agents offer SRMC.
- If not then prices depend on other agents behaviour
- Can model price process (and inflow process) and do stochastic DP (or SDDP) using this.
- HERO model does this for a single reservoir (**Pritchard, Philpott, Neame, *Math Programming*, 2004**)

# Dynamic programming

|          |   |  |
|----------|---|--|
| $x$      | = | level of stored water in reservoir   |
| $W_t$    | = | inflow to reservoir (assumed independent of $W_{t-1}$ )  |
| $s$      | = | generation stack submitted by generator  |
| $U_t(s)$ | = | water release from submitting stack $s$ in stage $t$   |
| $R_t(s)$ | = | profit earned from submitting stack $s$ in stage $t$   |
| $\alpha$ | = | discount factor  |
| $V_t(x)$ | = | optimal (random) future profit from $t$ to $\infty$<br>given a reservoir level $x$ at start of stage $t$ |
| $Y_t$    |   | market and inflow state  |

$$V_t(x) = \max_{s \in S} \{R_t(s, Y_t) + E[\alpha V_{t+1}(x - U_t(s) + W_t) | Y_t]\}$$

## Split formulation

$$g_t(\mu, \sigma, y) = \max_s R_t(s, y)$$

subject to  $\mu_t(s) = \mu$

$$\sigma_t(s)^2 \leq \sigma^2$$

$$V_t(x) = \max_{\mu, \sigma} \left\{ g_t(\mu, \sigma, Y_t) + \alpha E_{Z, W_t} [V_{t+1}(x - \mu - \sigma Z + W_t) \mid Y_t] \right\}$$

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# Computing $g(\mu, \sigma)$ with (random) price duration curves

Let  $p_i$  be breakpoints of piecewise linear price-duration curve and let  $A_i$  be the random slope of the segment between  $p_{i-1}$  and  $p_i$ .

Suppose  $A$  has mean  $a$  and covariance matrix  $V$ .

$$I_i = \int_{p_{i-1}}^{p_i} q(p) dp, \text{ for } i = 1, \dots, m.$$

$$g(\mu, \sigma) = \max \sum_{i=1}^m a_i \int_{p_{i-1}}^{p_i} p q(p) dp$$

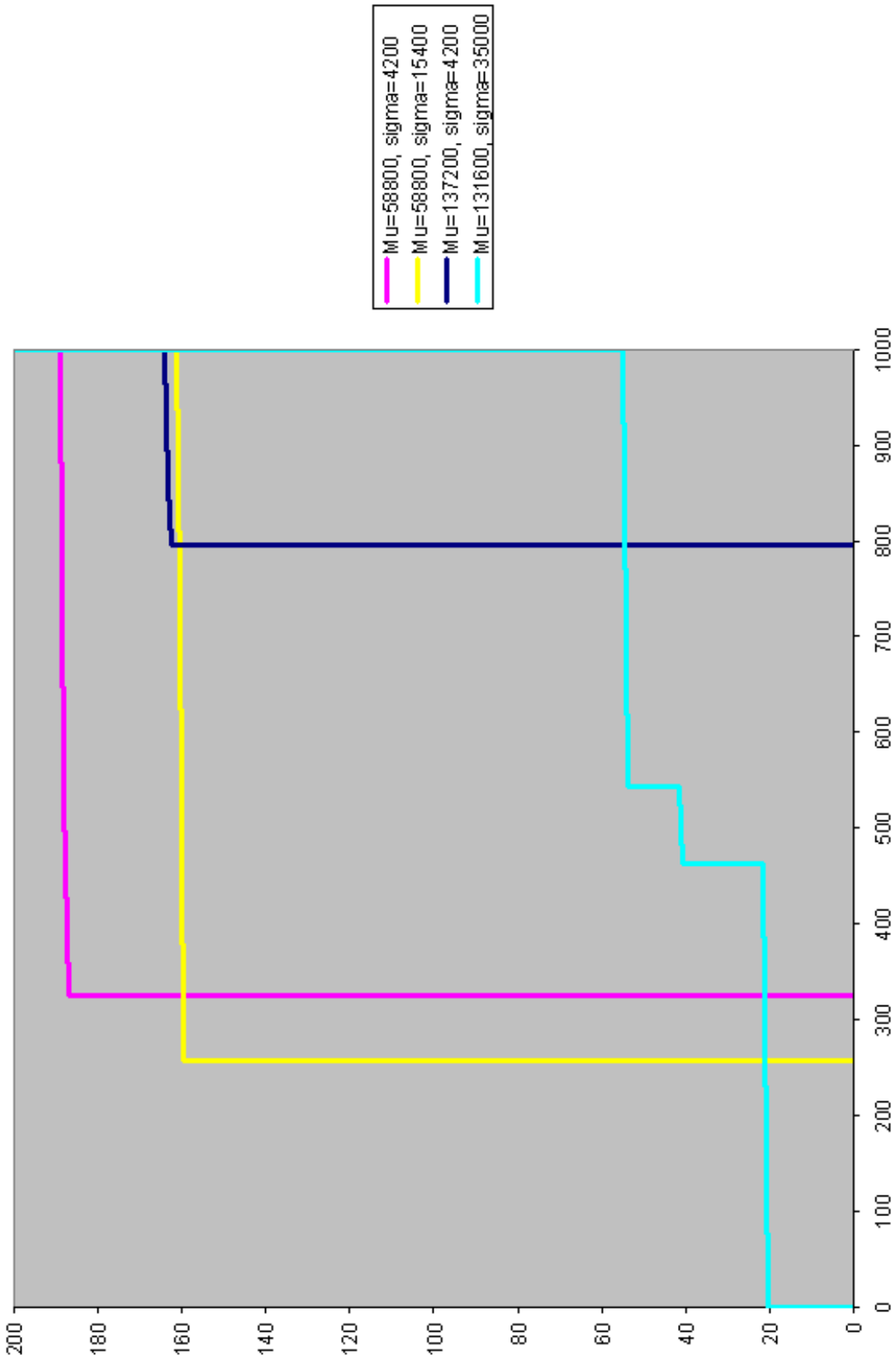
subject to  $q : [p_0, pm] \rightarrow [0, q_{\max}]$  is a non-decreasing function

$$I_i = \int_{p_{i-1}}^{p_i} q(p) dp, \quad i = 1, \dots, m,$$

$$a^\top I = \mu,$$

$$I^\top V I \leq \sigma^2,$$

# Solutions (from GAMS/MINOS)



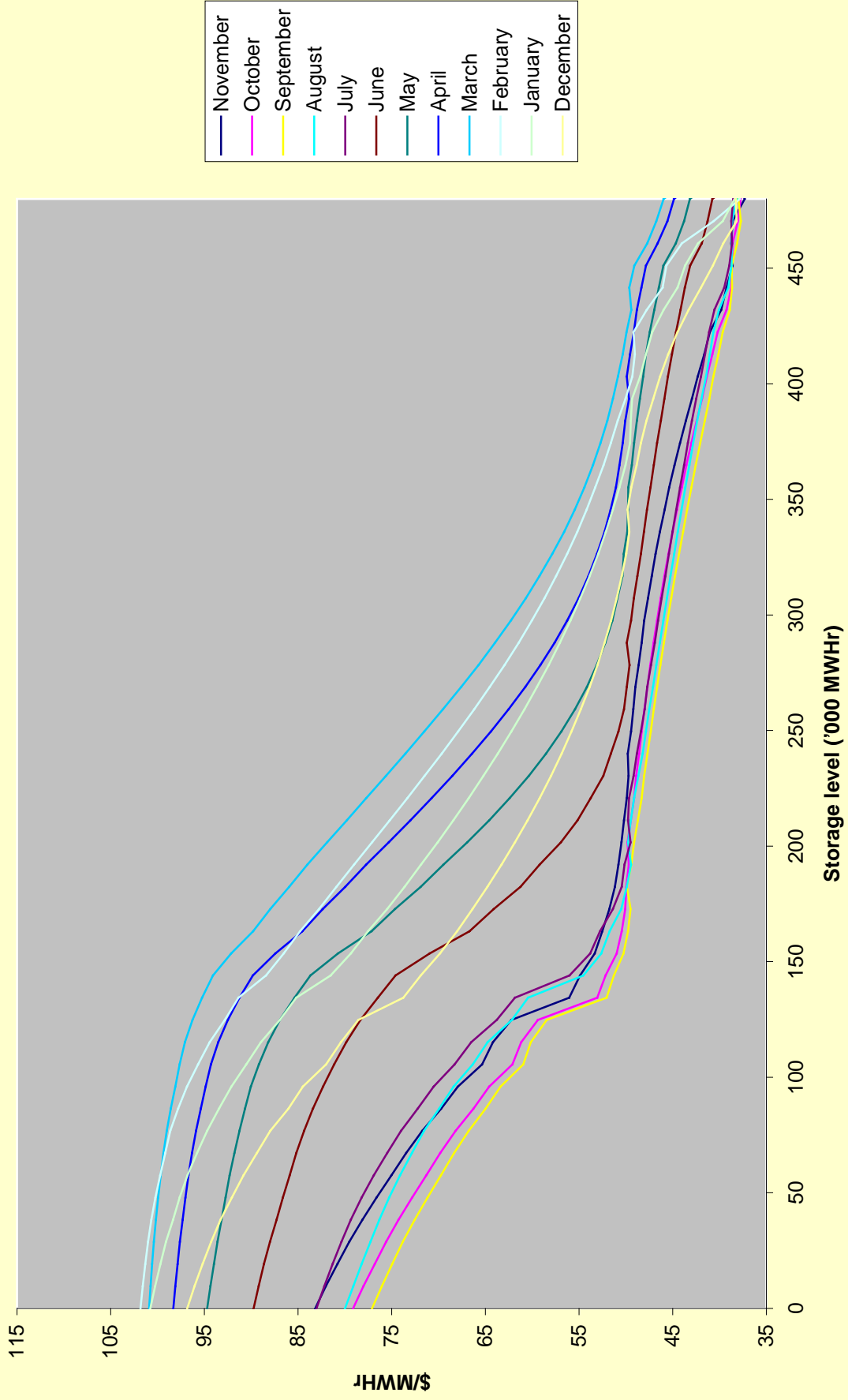
# Solutions to intra-week problem

Compute  $g_t(\mu, \sigma)$  offline for  $M = \{\mu_j : j \in J\}$  and  $S = \{\sigma_k : k \in K\}$

|       |      |       |       |       |       |       |       |       |       |       |       |       |
|-------|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|       | 8400 | 14000 | 19600 | 25200 | 30800 | 36400 | 42000 | 47600 | 53200 | 58800 | 64400 | 70000 |
| 4200  | 1.2  | 1.6   | 2.1   | 2.6   | 3.0   | 3.5   | 4.0   | 4.4   | 4.9   | 5.3   | 5.8   | 6.3   |
| 7000  | 1.5  | 2.0   | 2.4   | 2.9   | 3.3   | 3.8   | 4.3   | 4.7   | 5.2   | 5.6   | 6.1   | 6.5   |
| 9800  | 1.6  | 2.3   | 2.7   | 3.2   | 3.6   | 4.1   | 4.5   | 5.0   | 5.5   | 5.9   | 6.4   | 6.8   |
| 12600 | 1.6  | 2.5   | 3.0   | 3.4   | 3.9   | 4.4   | 4.8   | 5.3   | 5.7   | 6.2   | 6.6   | 7.1   |
| 15400 | 1.6  | 2.6   | 3.3   | 3.7   | 4.2   | 4.6   | 5.1   | 5.5   | 6.0   | 6.4   | 6.9   | 7.3   |
| 18200 | 1.6  | 2.6   | 3.5   | 4.0   | 4.4   | 4.9   | 5.3   | 5.7   | 6.2   | 6.6   | 7.1   | 7.5   |
| 21000 | 1.6  | 2.6   | 3.6   | 4.2   | 4.6   | 5.1   | 5.5   | 6.0   | 6.4   | 6.8   | 7.3   | 7.7   |
| 23800 | 1.6  | 2.6   | 3.6   | 4.4   | 4.9   | 5.3   | 5.7   | 6.2   | 6.6   | 7.0   | 7.5   | 7.9   |
| 26600 | 1.6  | 2.6   | 3.6   | 4.5   | 5.1   | 5.5   | 5.9   | 6.4   | 6.8   | 7.2   | 7.7   | 8.1   |
| 29400 | 1.6  | 2.6   | 3.6   | 4.5   | 5.3   | 5.7   | 6.1   | 6.6   | 7.0   | 7.4   | 7.8   | 8.2   |
| 32200 | 1.6  | 2.6   | 3.6   | 4.5   | 5.3   | 5.9   | 6.3   | 6.7   | 7.1   | 7.6   | 8.0   | 8.4   |
| 35000 | 1.6  | 2.6   | 3.6   | 4.5   | 5.3   | 6.0   | 6.5   | 6.9   | 7.3   | 7.7   | 8.1   | 8.5   |

Weekly revenue  $g_t(\mu, \sigma)$  in \$M for a range of  $\sigma_k$  (rows) and  $\mu_j$  (columns)

# Marginal water value by month



# SRMC function for a river chain

- Constraints affect feasible dispatch
- Tailor offers to meet river constraints
- Discretize prices, tribflows into bands
  - use price/tribflow scenarios
  - solve a stochastic LP
  - different models for block/station dispatch
  - can include two-hour rule, environmental constraints
- Model coded in AMPL/CPLEX for generic river chain  
(Philpott and Paulus, 2004)

# SRMC function for thermal unit

SRMC = fuel cost if unit commitment not counted

We can tailor offers to cover startup and shutdown costs

(Neame, Philpott, Pritchard, *Operations Research*, 2003)

# Price-making models

- Estimate the impact of offer on clearing price and dispatch
  - can be done by simulation (e.g. BOOMER code)
- Represent this as a

**market distribution function** (denoted  $\psi$ ).

$$\psi(q,p) = \Pr(\text{Not being fully dispatched if offer}(q,p))$$

# Market distribution functions

$$R(q, p) = qp + q_c(f - p) - C(q)$$

$$\begin{aligned} Z(q, p) &= \frac{\partial R(q, p)}{\partial q} \frac{\partial \psi(q, p)}{\partial p} - \frac{\partial R(q, p)}{\partial p} \frac{\partial \psi(q, p)}{\partial q} \\ &= (p - C'(q)) \frac{\partial \psi(q, p)}{\partial p} - (q - q_c) \frac{\partial \psi(q, p)}{\partial q} \end{aligned}$$

Optimal stack follows trajectory

$$Z(q, p) = 0$$



# Market distribution functions

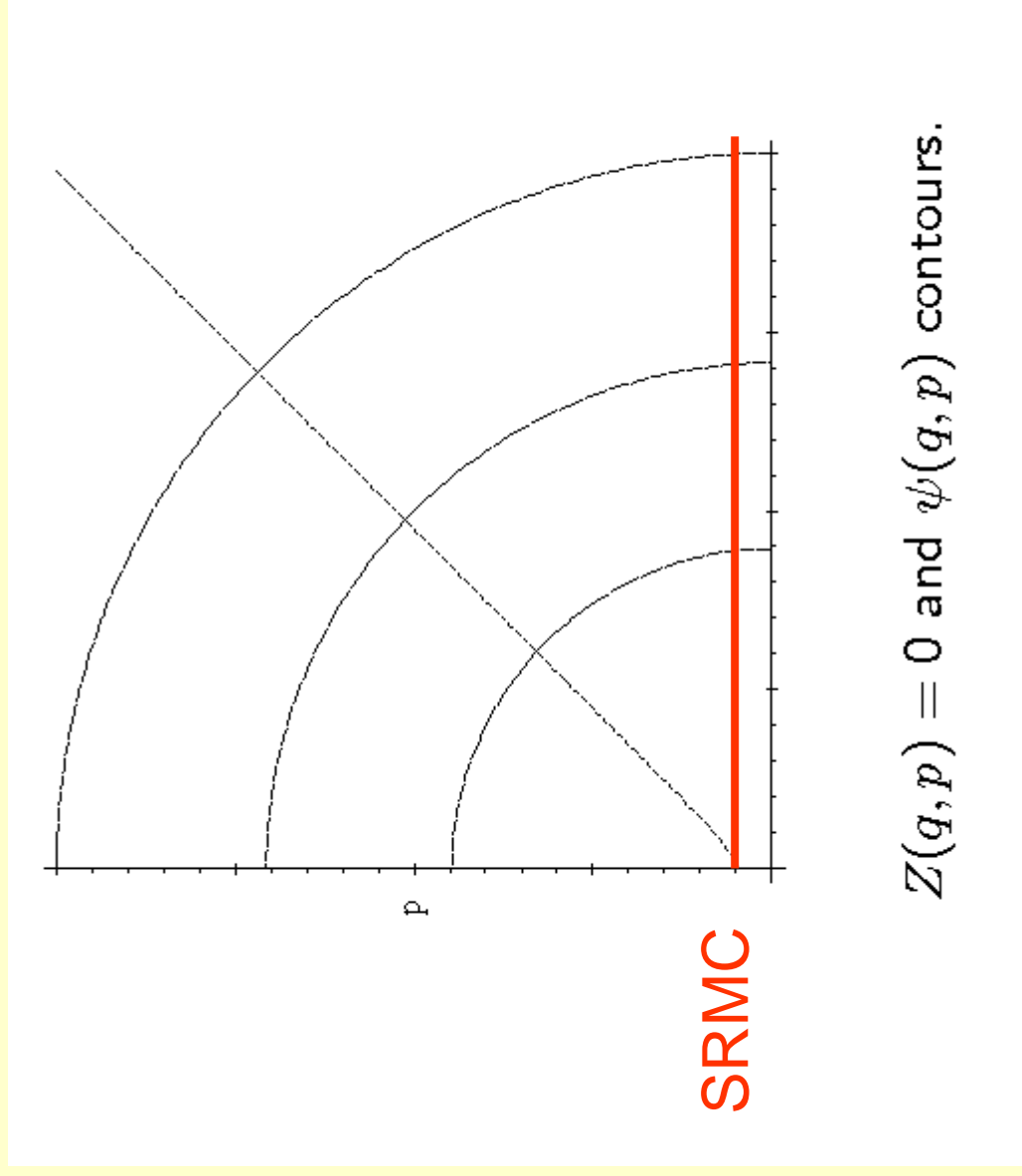
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Optimal stack follows trajectory

$$Z(q, p) = 0$$

# Market distribution functions



$Z(q, p) = 0$  and  $\psi(q, p)$  contours.

# Single unit with MDF

(Philpott and Schultz, 2004)

Stages  $k = 1, 2, 3, \dots, K$  with MDF  $\psi_k(q, p)$ .

States 0=stopped, 1=running

$$V_K(0) = V_K(1) = 0.$$

$$R_k = \max_s \int_s (pq - C(q) + q_c(f - p)) d\psi_k(q, p),$$

and

$$S_k = \int_0^\infty q_c(f - p) d\psi_k(0, p).$$

DP recursion

$$V_{k-1}(0) = \max\{S_k + V_k(0), R_k - U + V_k(1)\},$$

$$V_{k-1}(1) = \max\{S_k - D + V_k(0), R_k + V_k(1)\}.$$

# N identical units

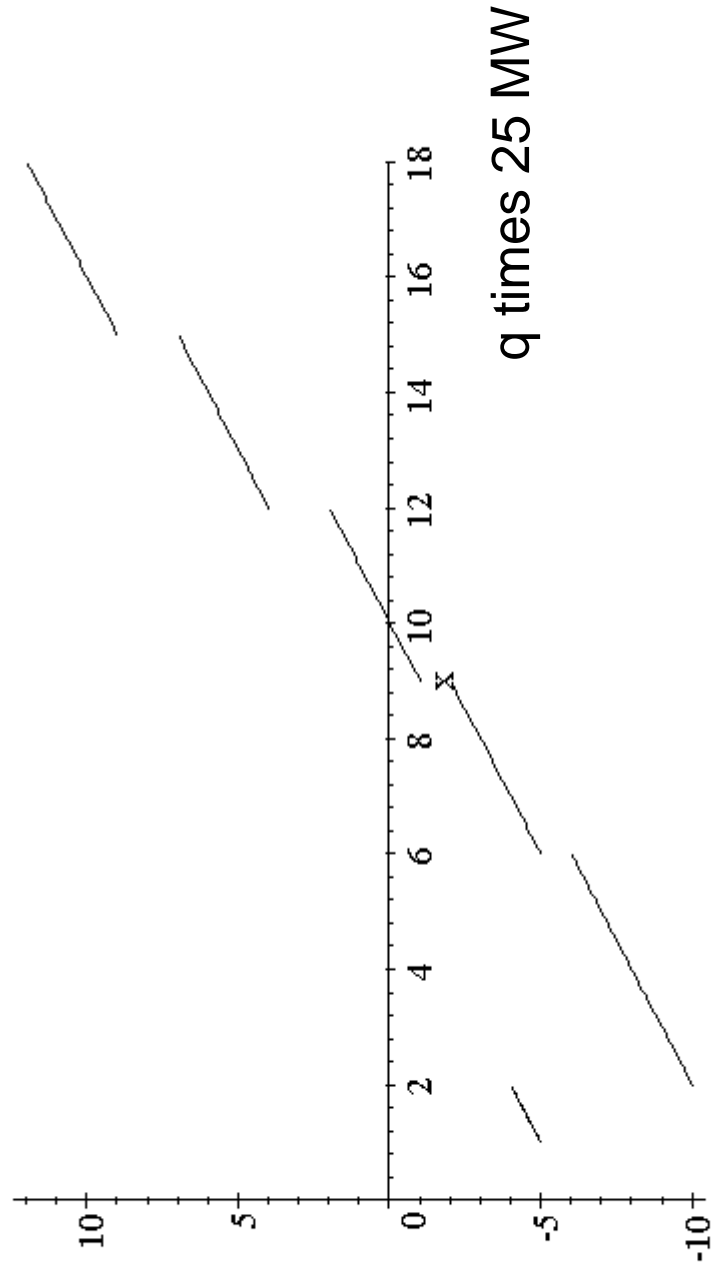
$$J(q) = \{j \mid j \text{ units can generate the amount } q\}$$

$$G_n(q) = \max_{j \in J(q)} \{V_k(j) - U[j - n]_+ - D[n - j]_+\}$$

$$R_{k-1}(n) = \max_s \int (pq + qc(f - p) - C(q) + G_n(q)) d\psi_k(q, p)$$

$$V_{k-1}(n) = \max\{S_k - nD + V_k(0), R_{k-1}(n)\}$$

# Expected Future Cost with 2 units on



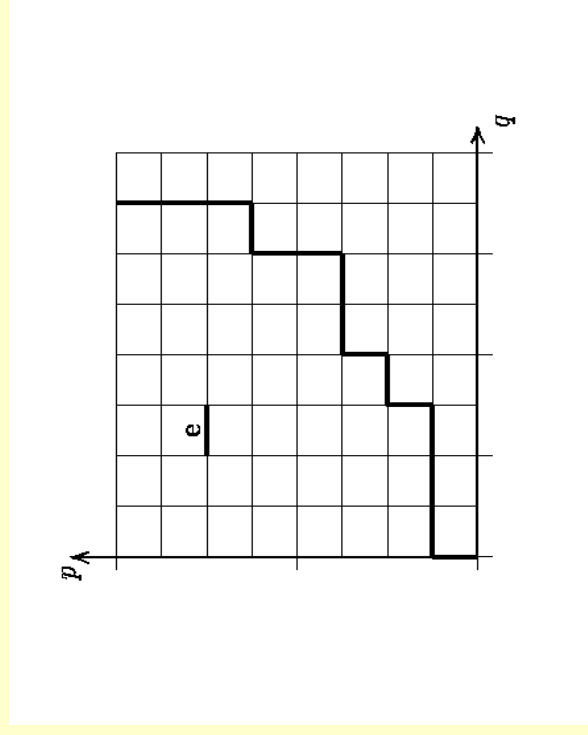
Plot of  $C_2(q)$

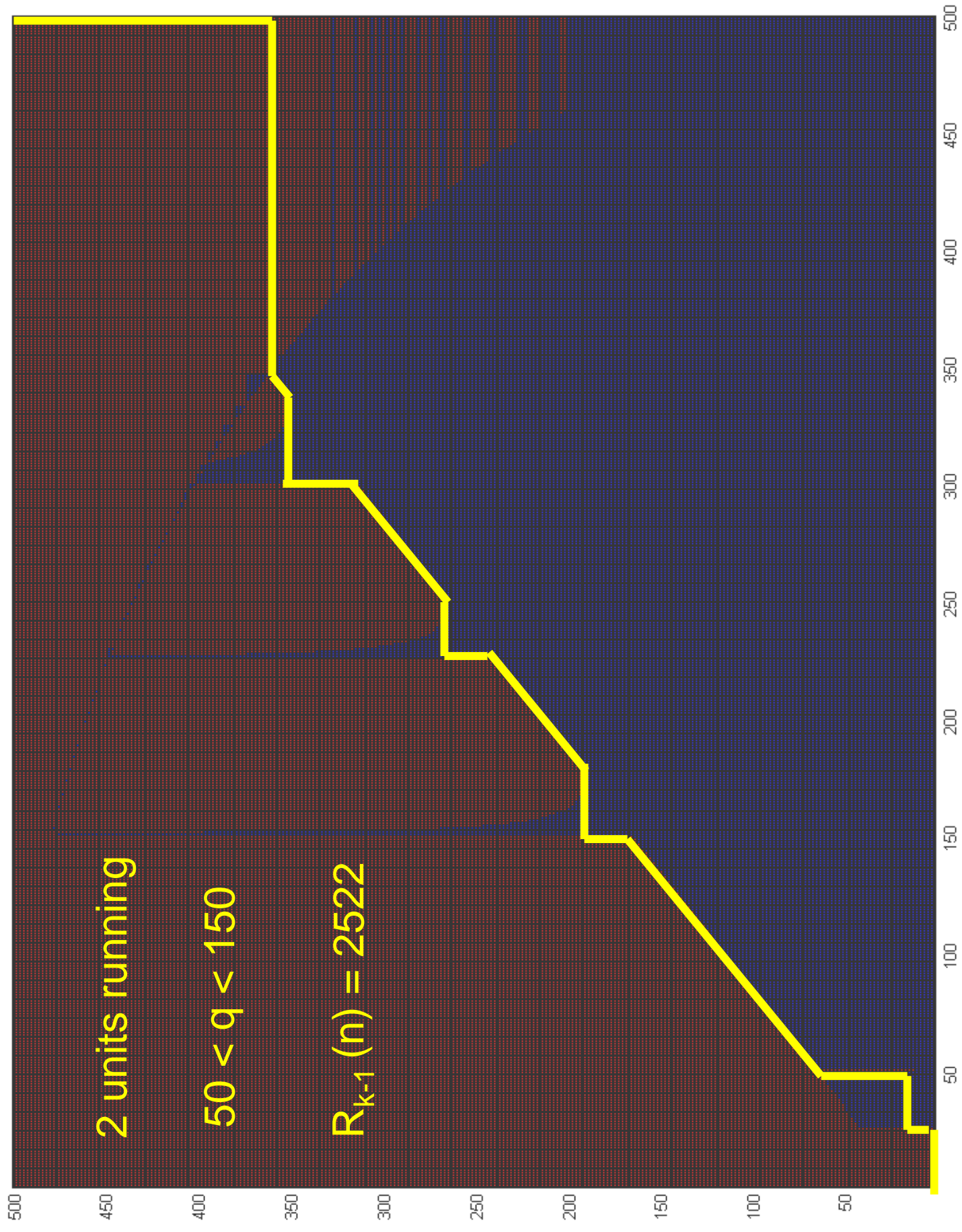
# Optimization technique

Work with a pre-determined grid.

$V(e)$  = expected payoff due to dispatches on edge  $e$ ,  
if  $e$  is included in the stack.  
(Psi function)

Given  $V(e)$  for each edge, can find the stack that includes the most value.

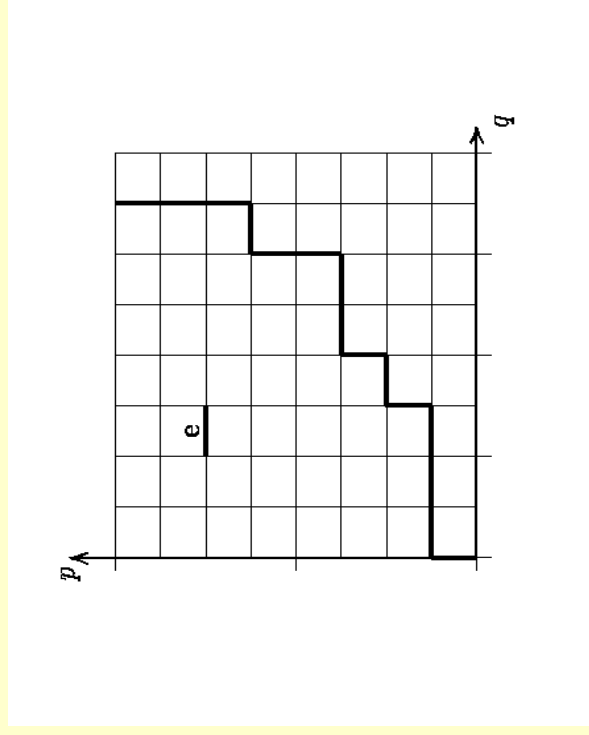




# Edge values from BOOMER

Generate scenarios of load and other agents offers.  
(antithetic sampling)

Estimate  $V(e)$  as the sample average payoff from  
dispatches on edge  $e$ .





p (\$/MWh)

|     |   |   |    |    |     |     |     |      |     |     |    |    |    |    |
|-----|---|---|----|----|-----|-----|-----|------|-----|-----|----|----|----|----|
| 240 | 1 | 5 | 15 | 35 | 26  | 21  | 19  | 27   | 19  | 12  | 9  | 5  | 3  | 3  |
| 220 | 0 | 0 | 3  | 9  | 17  | 22  | 16  | 15   | 23  | 15  | 10 | 7  | 4  | 4  |
| 200 | 0 | 1 | 12 | 6  | 120 | 31  | 141 | 147  | 52  | 66  | 64 | 56 | 43 | 30 |
| 190 | 0 | 0 | 1  | 3  | 5   | 7   | 11  | 1216 | 299 | 33  | 40 | 42 | 23 | 40 |
| 180 | 0 | 0 | 0  | 0  | 102 | 156 | 200 | 272  | 314 | 366 | 42 | 39 | 20 | 42 |
| 170 | 0 | 0 | 0  | 0  | 4   | 0   | 110 | 111  | 122 | 144 | 16 | 27 | 12 | 35 |
| 160 | 0 | 0 | 0  | 0  | 0   | 0   | 1   | 0    | 1   | 2   | 4  | 6  | 8  | 9  |
| 150 | 0 | 0 | 0  | 0  | 0   | 0   | 0   | 0    | 0   | 1   | 2  | 2  | 6  | 4  |
| 140 | 0 | 0 | 0  | 0  | 0   | 0   | 0   | 0    | 0   | 0   | 0  | 0  | 0  | 0  |
| 105 | 0 | 0 | 0  | 0  | 0   | 0   | 0   | 0    | 0   | 0   | 0  | 0  | 0  | 1  |
| 60  | 0 | 0 | 0  | 0  | 0   | 0   | 0   | 1    | 0   | 0   | 1  | 2  | 4  | 6  |
| 30  | 0 | 0 | 0  | 0  | 0   | 0   | 0   | 1    | 0   | 0   | 1  | 1  | 7  | 6  |
| 0   | 0 | 0 | 0  | 0  | 0   | 0   | 0   | 0    | 0   | 0   | 0  | 0  | 0  | 0  |

q (MW)

# Offers for HLY1

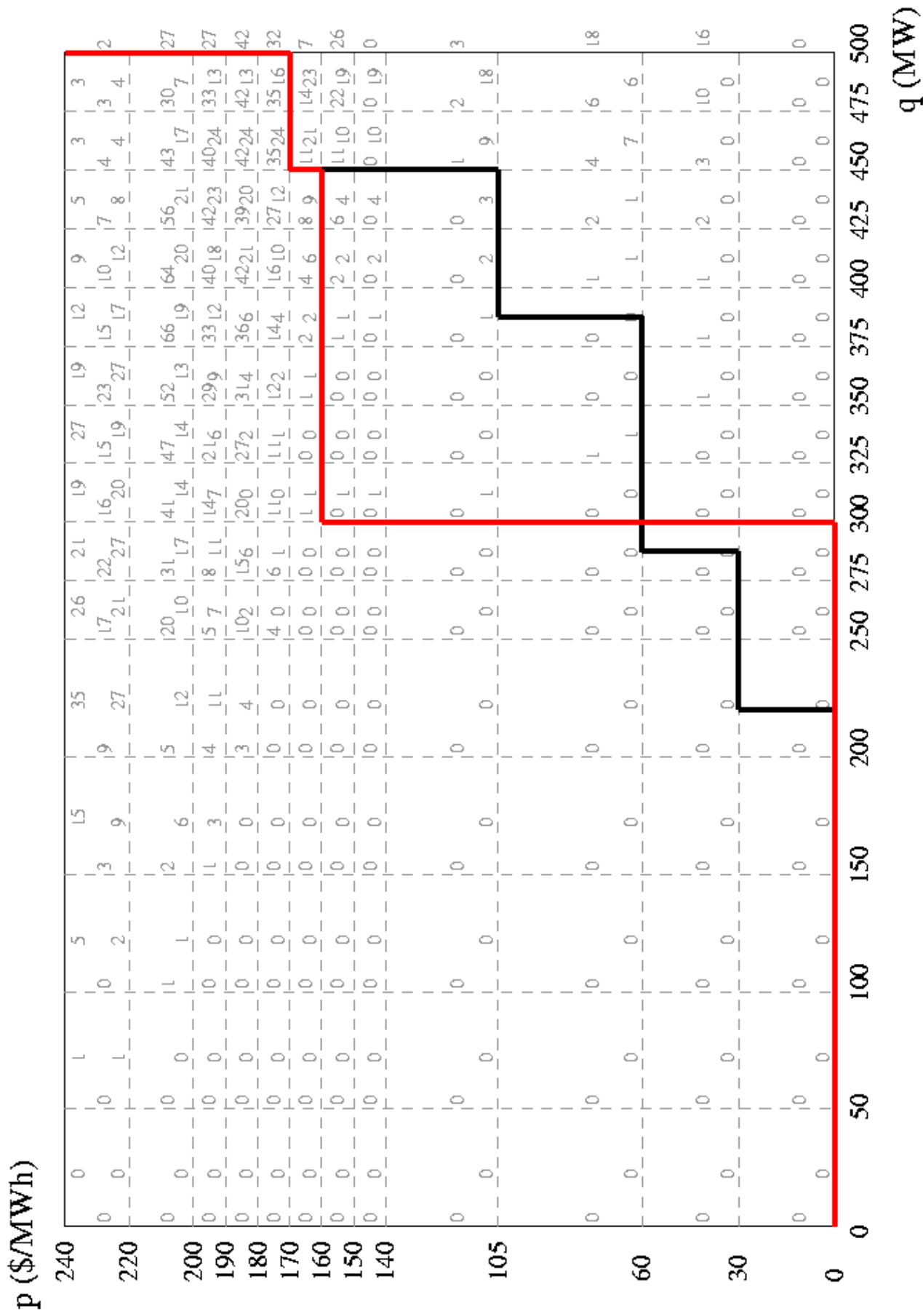
200 soehalios

# Generator's objective function

Owner of Huntly might have wanted to maximize

- revenue
  - HLY+TKU+RPO
- less generation cost
  - \$35/MWh
- less cost of own retail loads
  - 10% market share at MDN, OTA, HND, WKM, HAY, ISL
- As modified by contracts for differences
  - 100MW each at OTA, HAY, ISL, HWB; all at \$50/MWh.

(Numbers are illustrative only!)



# Offers for HLY1

200 scenarios  
Value of stack 38682

# Nash equilibrium models

## Classical model (Cournot)

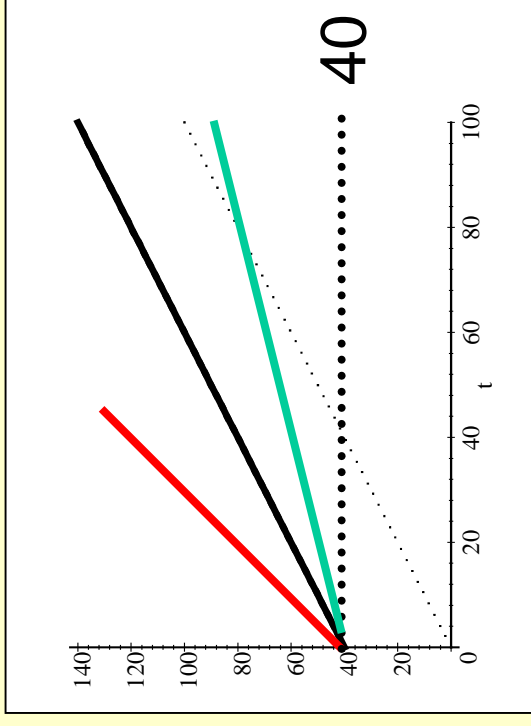
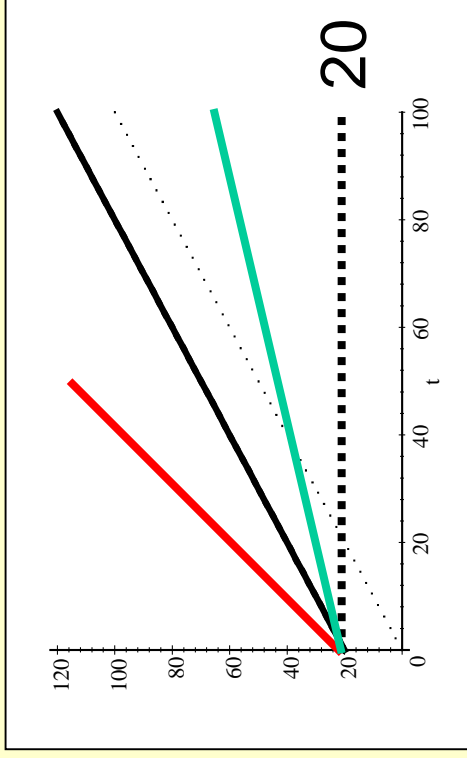
- Generator  $i$  offers quantity  $Q(i)$  at price 0
- Deterministic demand curve determines clearing price
- Transmission network can be modelled
- Non identical players can be modelled
- Solve using calculus or numerical method (PATH or MILES)

## Supply-function model (Klemperer & Meyer, 1989)

- Players offer supply functions (“marginal cost” curves)
- Demand can be elastic or inelastic (Anderson & Philpott, 2002)
- Uncertainty in demand ( $D(p) + h$ ,  $h$  a random shock)
- Mixed strategy s.f. equilibria exist in network models (Jofre, 2004)
- Difficult to model and compute with

# Inelastic SFE

Suppose two generators have fuel costs of \$20/MWh and \$40/MWh, and demand is random on  $[0, 200]$



# Equilibrium with a price cap

Suppose the Electricity Commission sets price cap of \$120/MWh

Two competing generators each with marginal cost \$20 and capacity 100 MW offer supply functions.

Demand randomly distributed on  $[0, 200]$

