Risk limiting dispatch (RLD) for renewable integration

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Outline

- Formulation of dispatch process
- Cost and risk
- Dynamic programming
- Risk limiting dispatch (RLD)
- Examples

Net demand $D(t) = L(t) - W(t)$

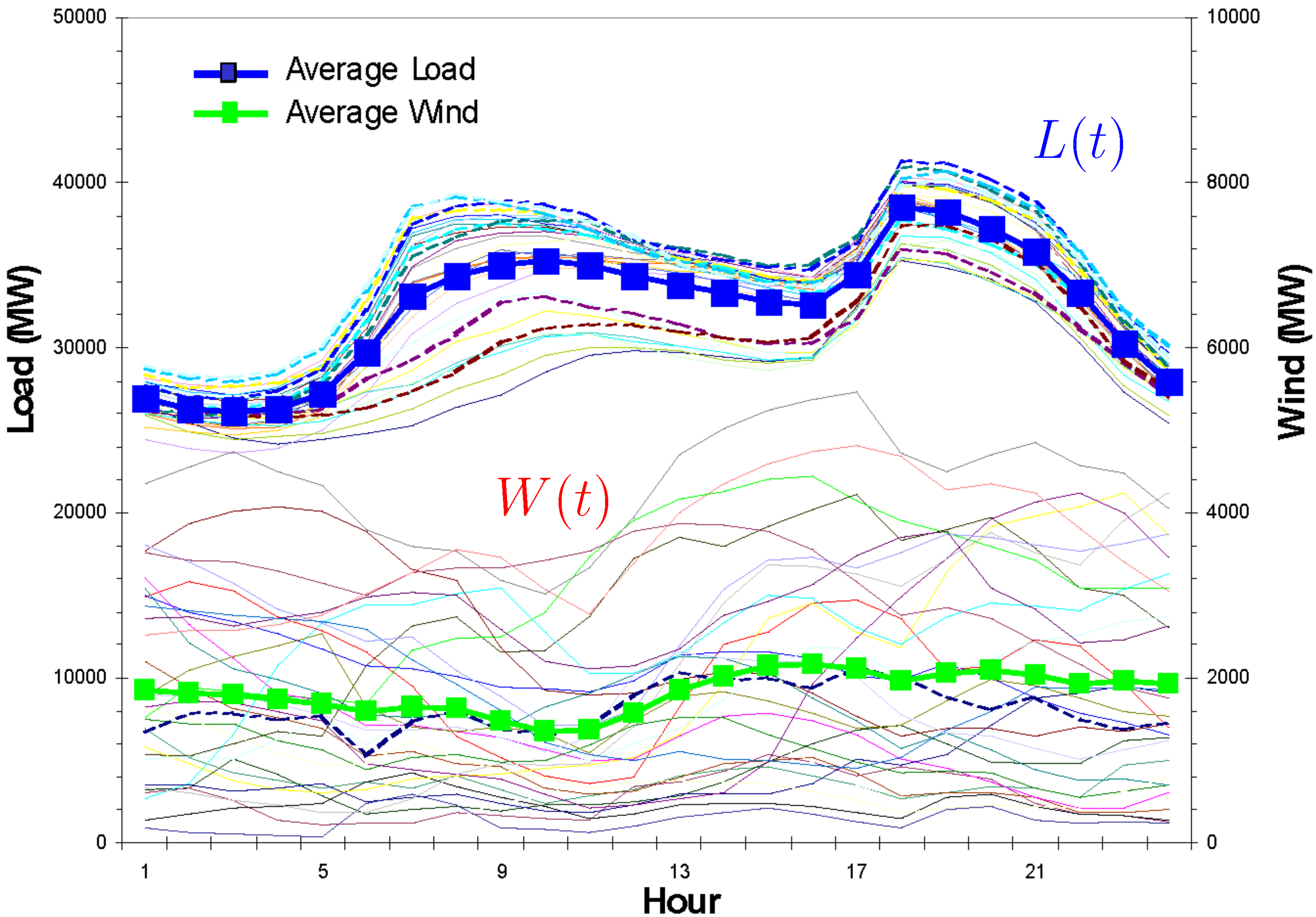
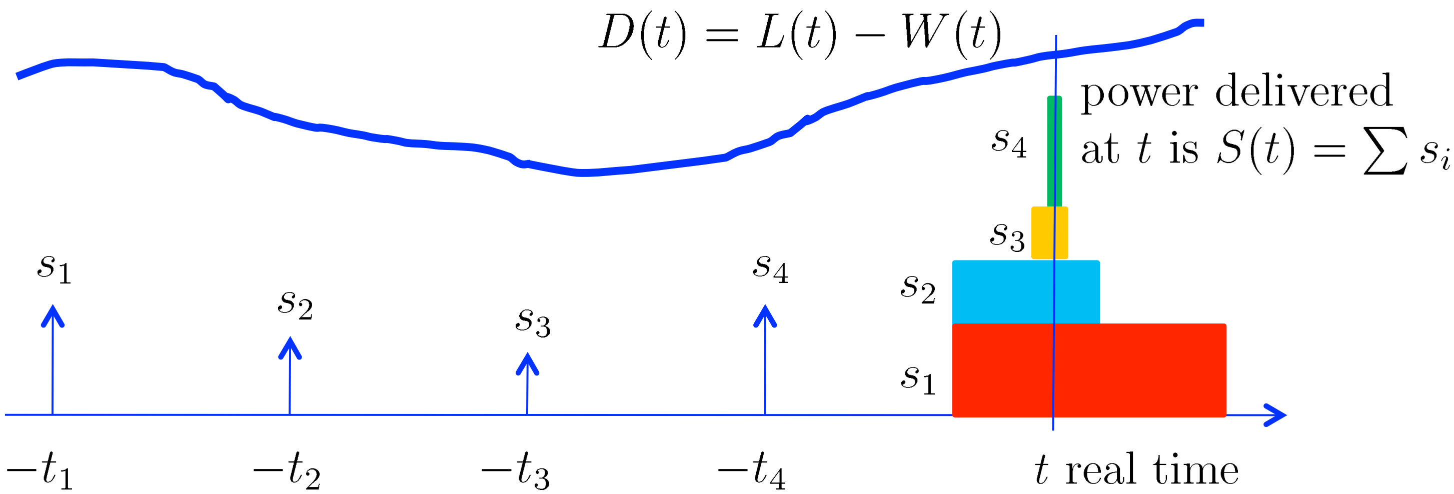


Figure 7. All Systemwide Daily Load and Wind Profiles for January 2002.

SO's dispatch procedure

- SO buys forward energy blocks to match net demand $D(t) = L(t) - W(t)$
- Blocks get shorter as real time approaches



Reserve capacity

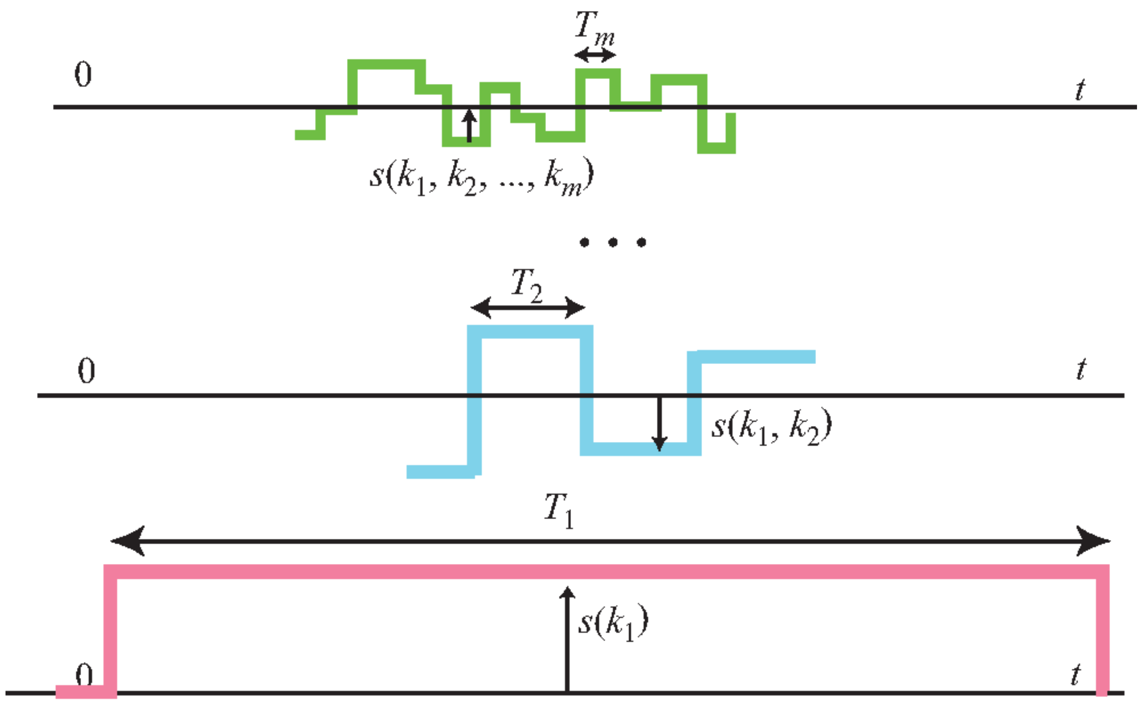
- SO also buys reserve capacity – a call option

- Modeled as purchase of forward block, followed by sale if capacity is not utilized:
  Price of reserve = purchase price – sale price.

- Hence SO constructs supply $S(t)$ to match $D(t)$ by buying and selling forward energy blocks

Constructing supply

- Stack blocks of duration $T_1, \cdots, T_m$ that are bought or sold in m forward markets to create supply $S(t)$



$$T_m = T_{m-1}/N_m$$

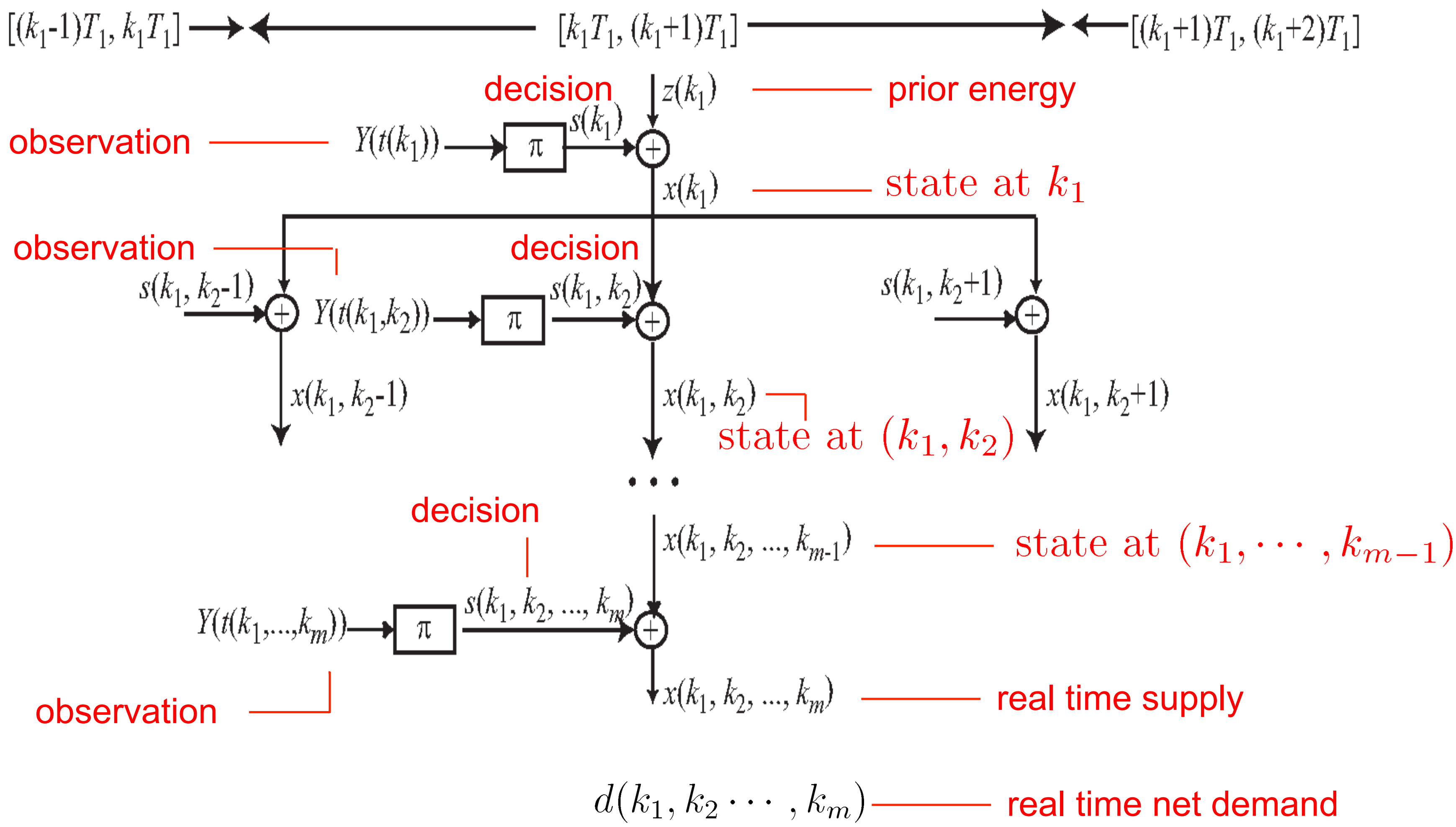
$$T_2 = T_1/N_2$$

$$T_1 = 1 \text{ hour say}$$

$$S(t) = s(k_1) + s(k_1, k_2) + \cdots + s(k_1, \cdots, k_m),$$

$$t \in k_1 T_1 + \cdots + k_{m-1} T_{m-1} + [k_m T_m, (k_m + 1) T_m]$$

General setup: m stages



State

$x(k_1, \cdots, k_j) =$ power secured after $s(k_1, \cdots, k_j)$

$$x(k_1, \cdots, k_{j+1}) = x(k_1, \cdots, k_j) + s(k_1, \cdots, k_{j+1}), \\ j = 0, \cdots, m-1$$

$z(k_1)$ is initially secured power.

'Control' is $s(k_1, \cdots, k_j) > 0$ (buy) or < 0 (sell).

Objective: want $x(t) \approx$ net load $D(t) = L(t) - W(t)$

Energy cost + Mismatch penalty

buying selling

$$J(\pi) = \mathbb{E}\sum T_j[c^+(k_1,\cdots,k_j)s_+(k_1,\cdots,k_j) + c^-(k_1,\cdots,k_j)s_-(k_1,\cdots,k_j)]$$
$$+ \sum T_m g(d(k_1,\cdots,k_m), x(k_1,\cdots,k_m))$$

mismatch penalty

Risk-limiting dispatch (RLD) minimizes $J(\pi)$

$\pi = \{s(k_1,\cdots,k_j)\}$, $s(k_1,\cdots,k_j)$ is function of $Y(t(k_1,\cdots,k_j))$

Could have cost $= \sum C(k_1,\cdots,k_j,s)$, C convex, $s \in R$.

Mismatch penalty examples

Value of lost load (VOLL)

$$g(d(k_1,\cdots,k_m),x(k_1,\cdots,k_m)) \\ = \gamma^+(k_1\cdots k_m)[d(k_1,\cdots,k_m)-x(k_1,\cdots,k_m)]_+$$

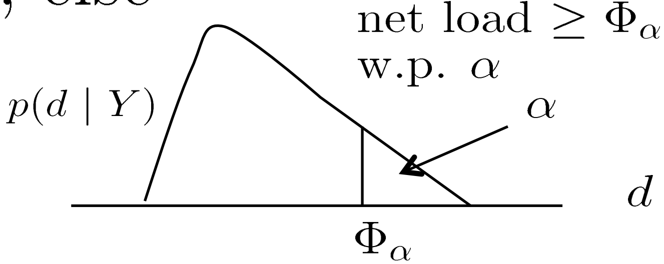
Loss of load probability (LOLP) at most α:

$$P\{d(k_1,\cdots,k_m)\geq x(k_1,\cdots k_m)\mid Y(t(k_1,\cdots,k_m)\}\leq\alpha$$

Equivalent to $g(d,x)$ with

$g(d,x)=\infty$ if $P\{d\geq x\mid Y\}>\alpha$; 0, else

or if $x\leq\Phi_\alpha$



Conditional quantity at risk

$$g(d,x)=c^+\mathrm{E}\{d-x\mid d-x\geq\Phi_\alpha(d-x)\}$$

All $g(d,x)$ convex in x

Principle of optimality

Value function = min cost-to-go is

$$J^*(x, k_1 \cdots k_j) = \min_\pi J(\pi, x, k_1 \cdots k_j)$$

Lemma For all x, j, $k_1 \cdots k_j$:

$$J^*(x, k_1 \cdots k_j) = \inf\{T_{j+1}[c^+(k_1 \cdots k_{j+1})s_+ + c^-(k_1 \cdots k_{j+1})s_-] \\ + T_{j+2} \sum_{k_{j+2}=0}^{N_{j+2}-1} \mathrm{E}\{J^*(x+s, k_1 \cdots, k_{j+1}) \mid Y(t(k_1 \cdots k_{j+1})\}.$$

The boundary condition is

$$J^*(x, k_1 \cdots k_m) = T_m \mathrm{E}\{g(d(k_1, \cdots, k_m), x) \mid Y(t(k_1 \cdots k_m))\}.$$

Moreover, minimizing s_+, s_- is the optimal decision $s_+^*(k_1 \cdots k_{j+1}), s_-^*(k_1 \cdots k_{j+1})$.

Main result

1. $J^*(x, k_1 \cdots k_j)$ is convex in x w.p. 1

2. $\exists$ thresholds $\phi_+(k_1 \cdots k_{j+1}) \ < \ \phi_-(k_1 \cdots k_{j+1})$:

   $$s_+^*(k_1 \cdots k_{j+1}) = [\phi_+ - x]_+ \ , \ s_-^*(k_1 \cdots k_{j+1}) = [\phi_- - x]_- \ .$$

3. $\phi_+, \ \phi_-$ are functions of $Y(t(k_1 \cdots k_{j+1}))$, independent of x:
   $-\nabla \hat{J}(\phi_+) = c^+, \quad -\nabla \hat{J}(\phi_-) = c^-$

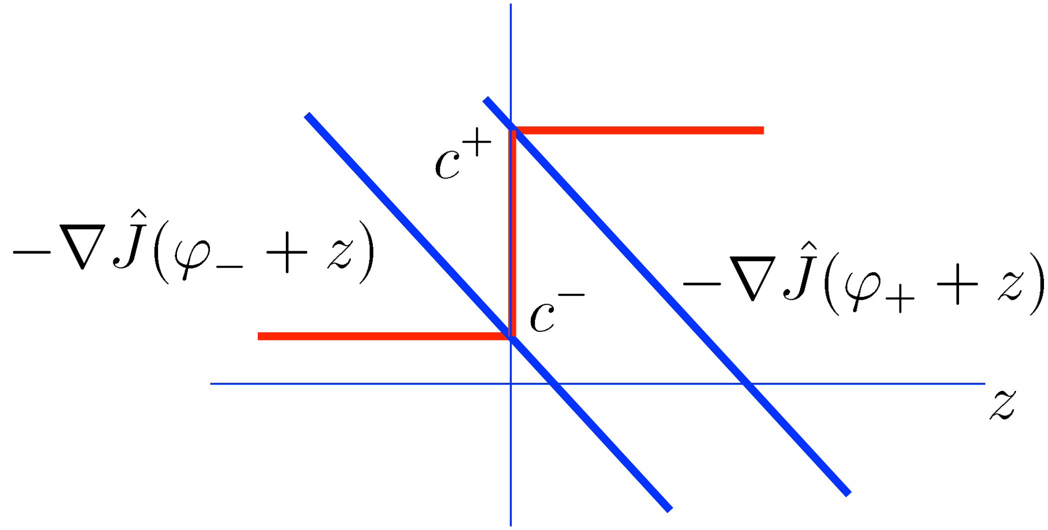
   $\hat{J} = \mathrm{E}\{J^*(z, k_1 \cdots k_{j+1}) \mid Y(t(k_1 \cdots k_{j+1}))\}$
   $c^+ =$ buy price , c$^-$ = sell price

4. $J^*(x, k_1 \cdots k_j) = c^+ s_+^* + c^- s_-^* + \hat{J}(x + s_+^* + s_-^*)$

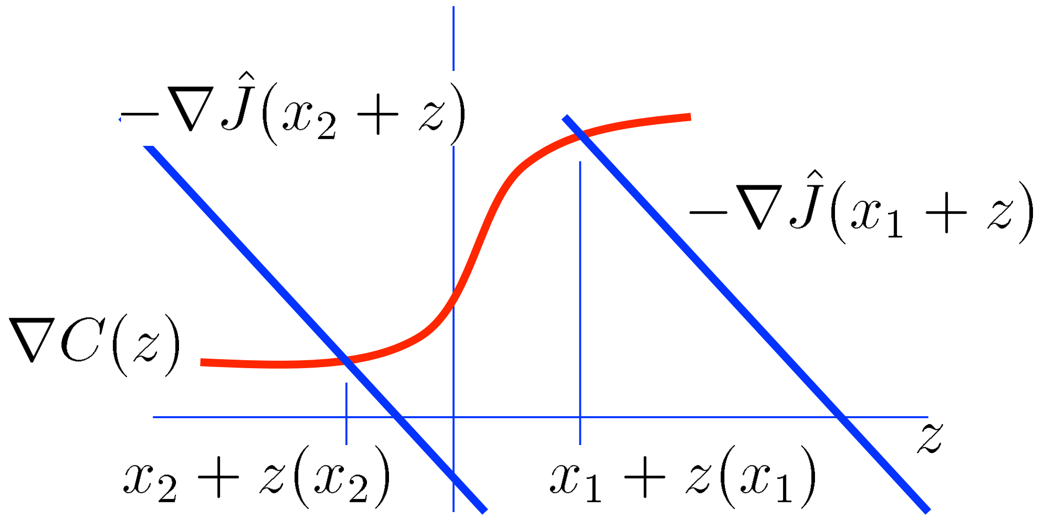
5. $J^*(x, k_1 \cdots k_m) = T_m \mathrm{E}\{g(d(k_1, \cdots, k_m), x) \mid Y(t(k_1 \cdots k_m))\}.$

Threshold rule

constant
prices



variable
prices



RLD

1. SO receives observations $Y(t(k_1, \cdots, k_j))$

2. SO computes thresholds $\phi_{\pm}(k_1, \cdots, k_{j+1})$

3. SO buys/sells $s = s(k_1, \cdots, k_{j+1})$ so $s + x \in [\phi_+, \phi_-]$

Target reserve

Gaussian errors

Assumption

Real time net demand $d(k_1, \cdots, k_m)$ expressed as
$d(k_1, \cdots, k_m) = \bar{d}(k_1, \cdots, k_m) + \epsilon(k_1) + \cdots + \epsilon(k_1, \cdots, k_m)$

- ☐ $\bar{d}(k_1, \cdots, k_m)$ is $\mathcal{Y}(t(k_1))$ adapted
- ☐ $\epsilon(k_1, \cdots, k_j)$ is $\mathcal{Y}(t(k_1, \cdots, k_{j+1}))$ adapted; $\perp \mathcal{Y}(t(k_1, \cdots, k_j))$
- ☐ $\epsilon(k_1), \cdots, \epsilon(k_1, \cdots, k_m)$ are independent Gaussian r.v. with zero mean and standard deviation $\sigma(k_1, \cdots, k_j)$.

Forecast of $d(k_1, \cdots, k_m)$ at time $t(k_1, \cdots, k_j)$ is
$\mu(k_1, \cdots, k_j) = \bar{d}(k_1, \cdots, k_m) + \epsilon(k_1) + \cdots + \epsilon(k_1, \cdots, k_{j-1})$.
Forecast error is
$d(k_1, \cdots, k_m) - \mu(k_1, \cdots, k_j) = \epsilon(k_1, \cdots, k_j) + \cdots + \epsilon(k_1, \cdots, k_m)$
is Gaussian with zero mean and variance
$\sigma^2(k_1, \cdots, k_j) + \cdots + \sigma^2(k_1, \cdots, k_m)$.

Thresholds in Gaussian case

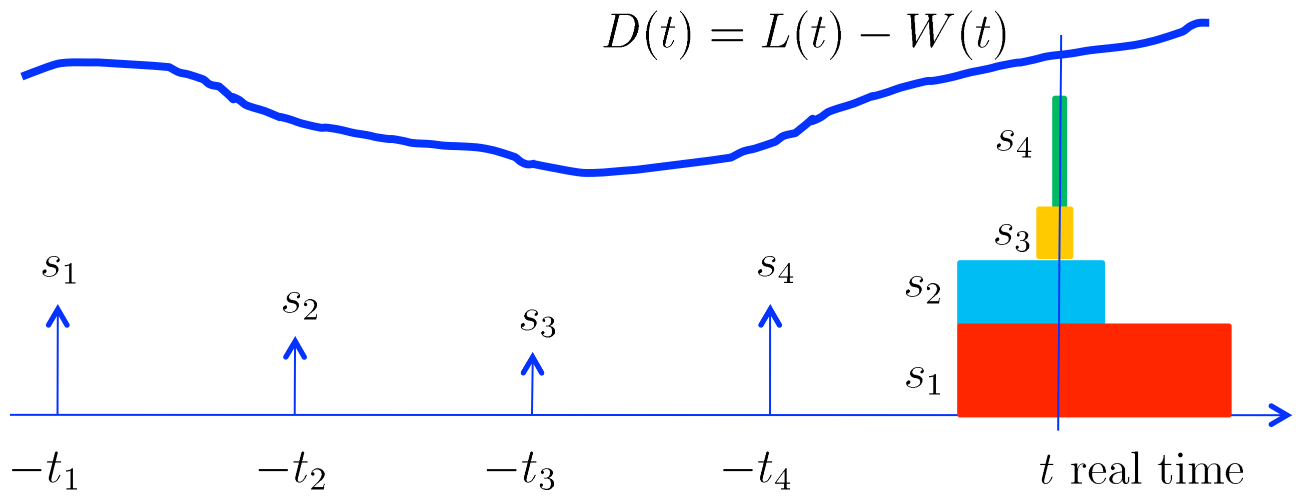
Theorem The thresholds are given by

$$\phi_{\pm}(k_1, \cdots, k_j) = \mu(k_1, \cdots, k_j) + \Delta_{\pm}(k_1, \cdots, k_j),$$

in which μ is the forecast and the constant risk premiums $\Delta_{\pm}$ can be computed ahead of time.

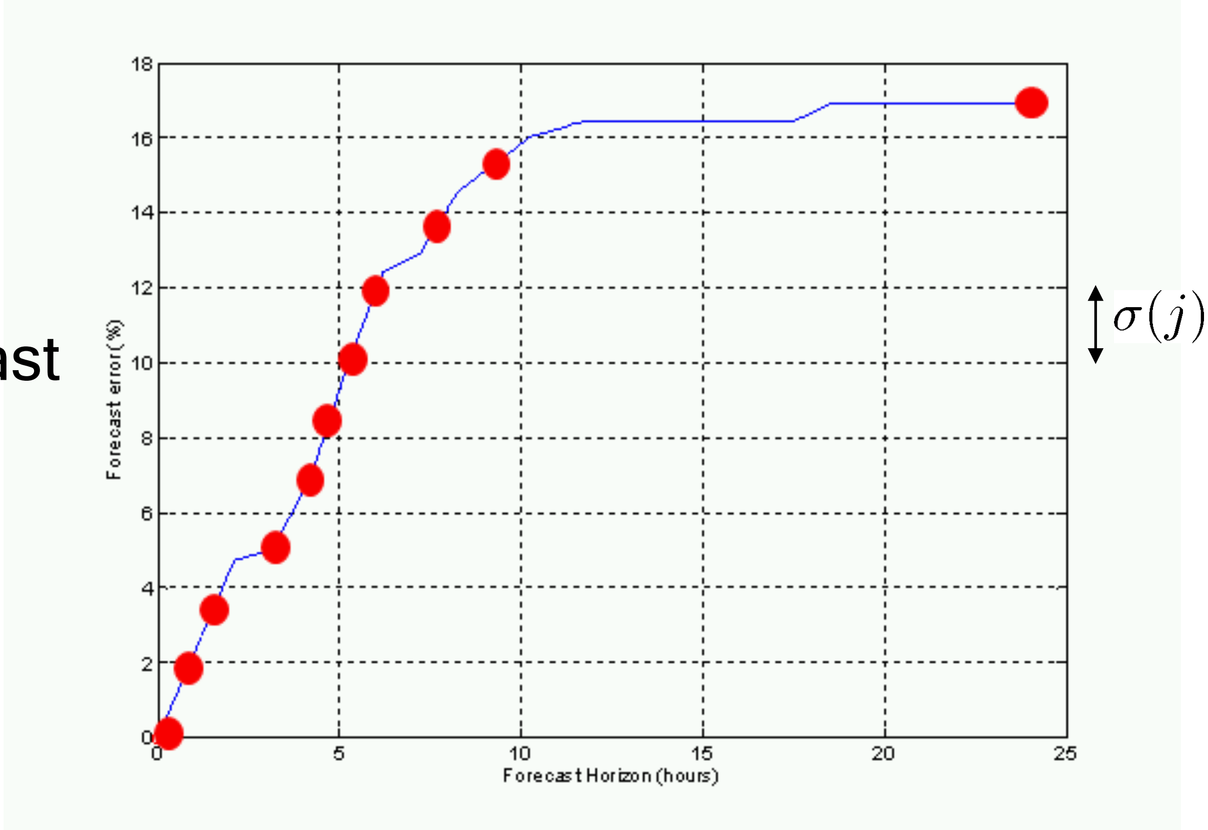
Examples

- In the examples, all blocks have same duration, only purchases allowed, so $s_- = 0$



Examples: up to 10 stages

Forecast error



Cost: $c(t) = A + Be^{-\gamma t}$, t is time horizon, with

$$c(24) = \$52,\ c(5min) = \$60,\ c(0) = \$72.$$

Example A

1. 2-stages: 1 (24-ahead) and 10 (real-time).
2. 10-stages: all stages in the plot.
3. Oracle: d is known, so purchases $s(1) = d_+$ lowest price.

Procedure for computing RLD

1. Select any realization of $d/d_{max} = d \in [-1, 1]$.
2. Generate 100 samples of errors $\epsilon(j) \approx (0, \sigma^2(j))$.
3. For each d and error sample calculate forecast $\mu(j)$, optimal policy $\{s^*(j)\}$, and minimum cost $\mathbb{E}[c(1)s^*(1) + \cdots + c(m)s^*(m)]$

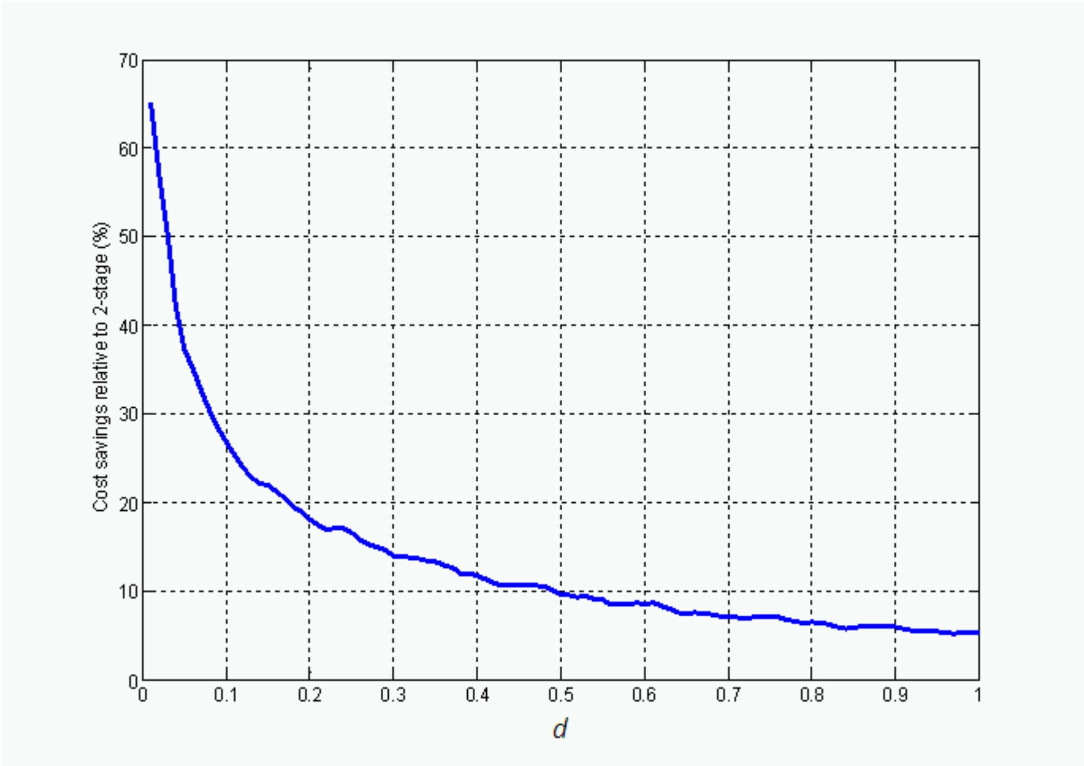
Result for Example A (1/4)

Normalized cost $= \text{actual}/\$72$

$\$52/\$72 = 0.72$

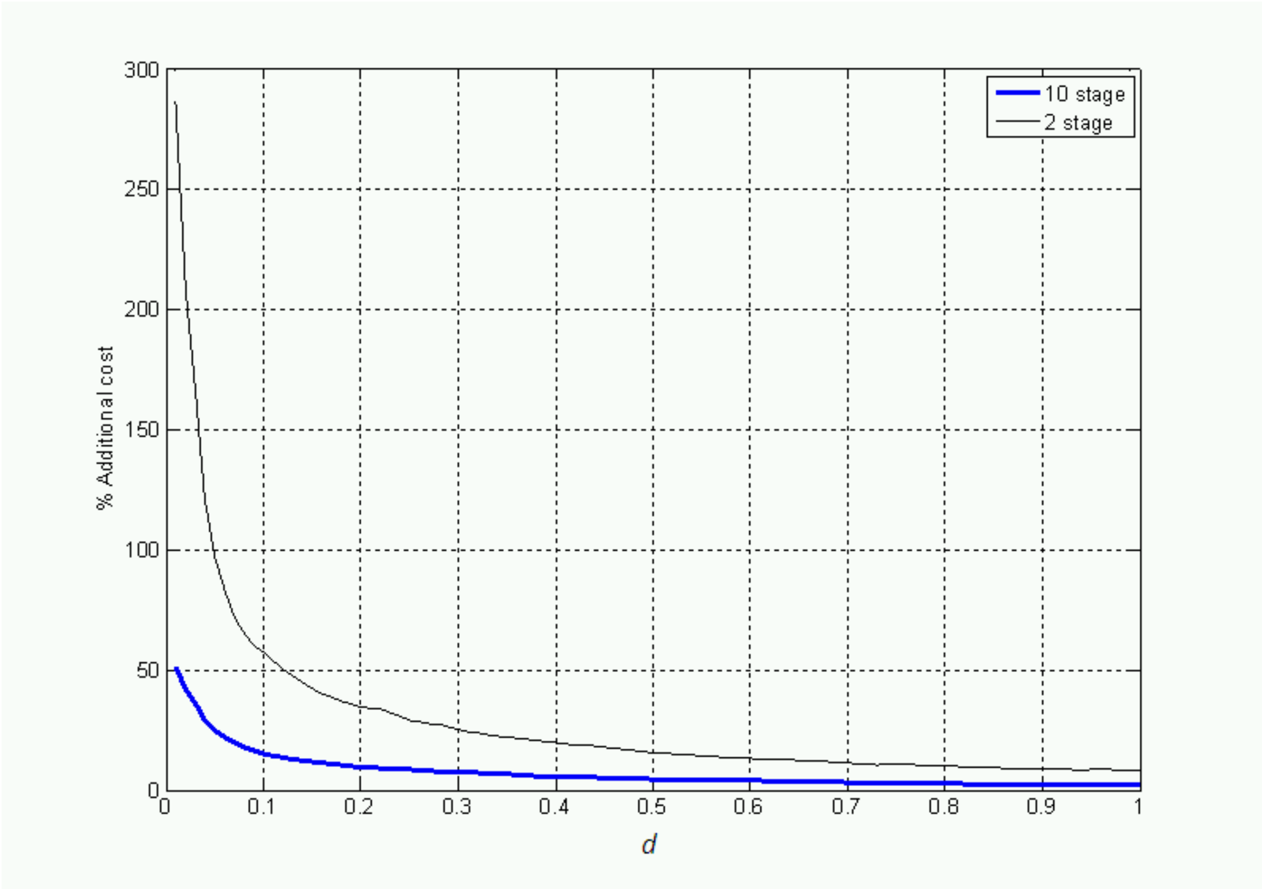
10-stage cost - 2-stage cost $= 0.05 \times 72 =$ $3.6 per MWh

Result for Example A (2/4)



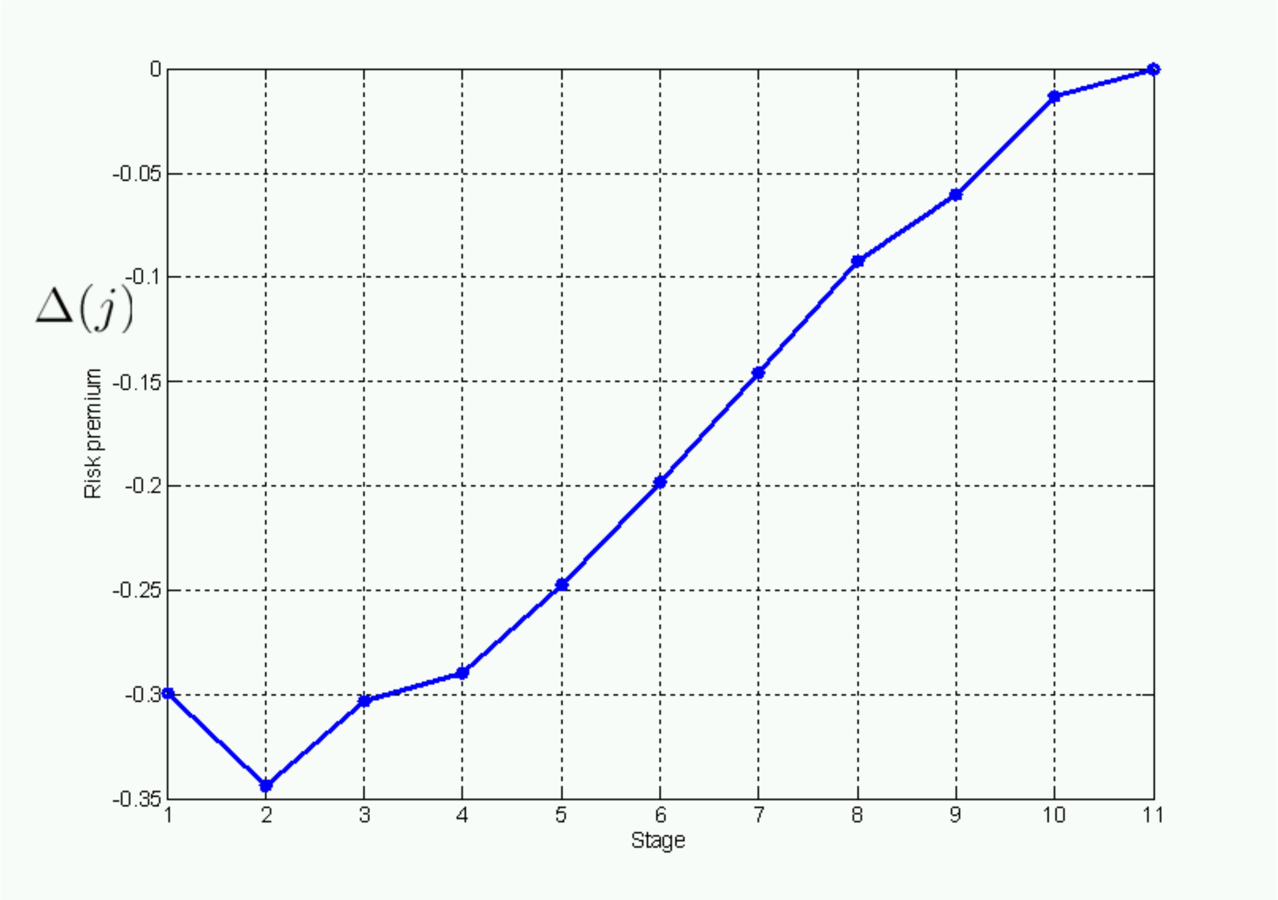
Rel savings = (2-stage - 10-stage)/2-stage approaches 70% as $d \to 0$

Result for Example A (3/4)



Additional cost relative to oracle cost.

Result for Example A (4/4)



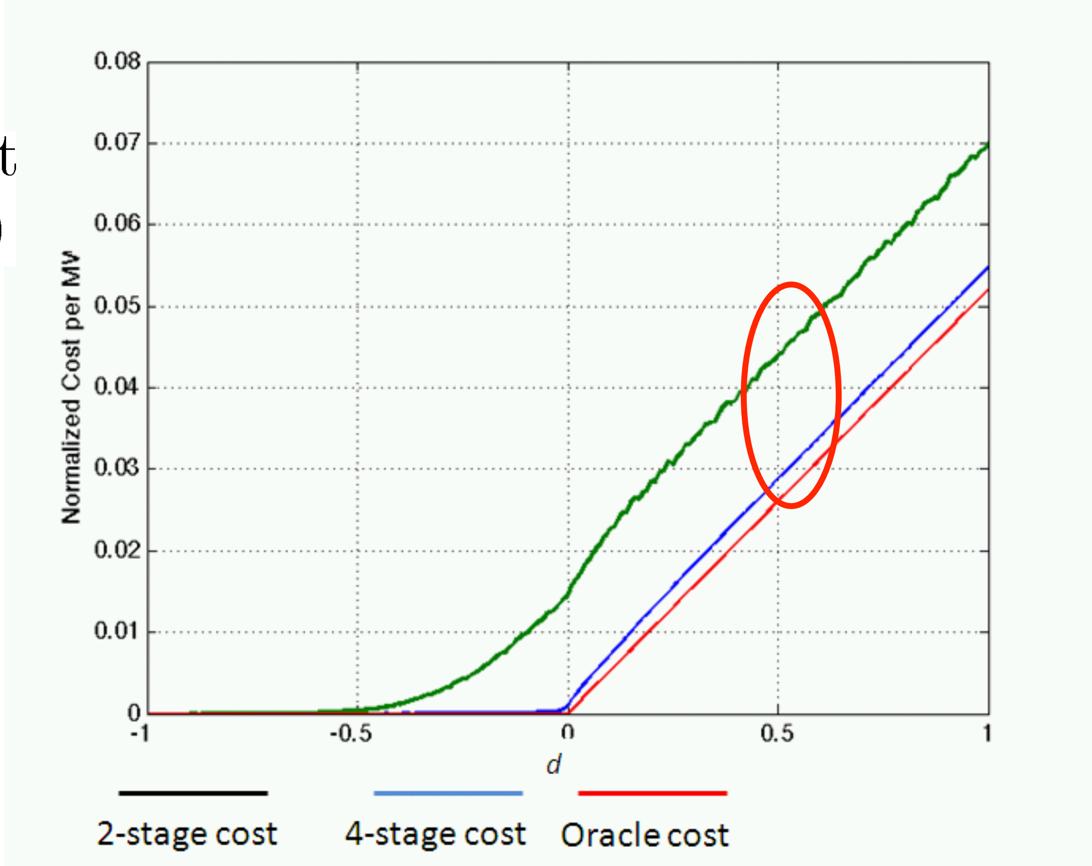
Risk premium $\Delta(j) < 0$, $\rightarrow 0$ as real time approaches

10-stage strategy purchases less than demand forecast!

Example B VOLL penalty

1. 2-stages: 24-ahead$52 and real-time VOLL $1000.
2. 4-stages: 24-ahead $52, 1-hr $60, 15-min $72, VOLL $1000

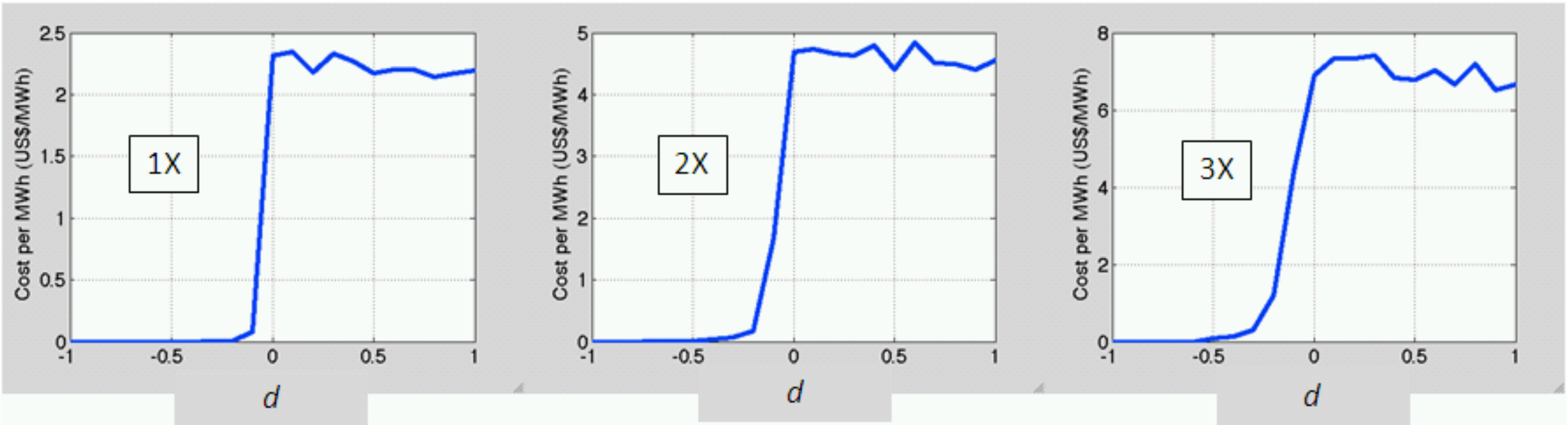
Normalized cost = actual/$1000



2-stage cost - 4-stage cost ≈ $15 per MWh

Example C: effect of better forecast

1. 3-stages: 24-ahead \$52, 1-hr \$60, VOLL \$1000.
2. 4-stages: 24-ahead \$52, 1-hr \$60, 15-min \$72, VOLL \$1000

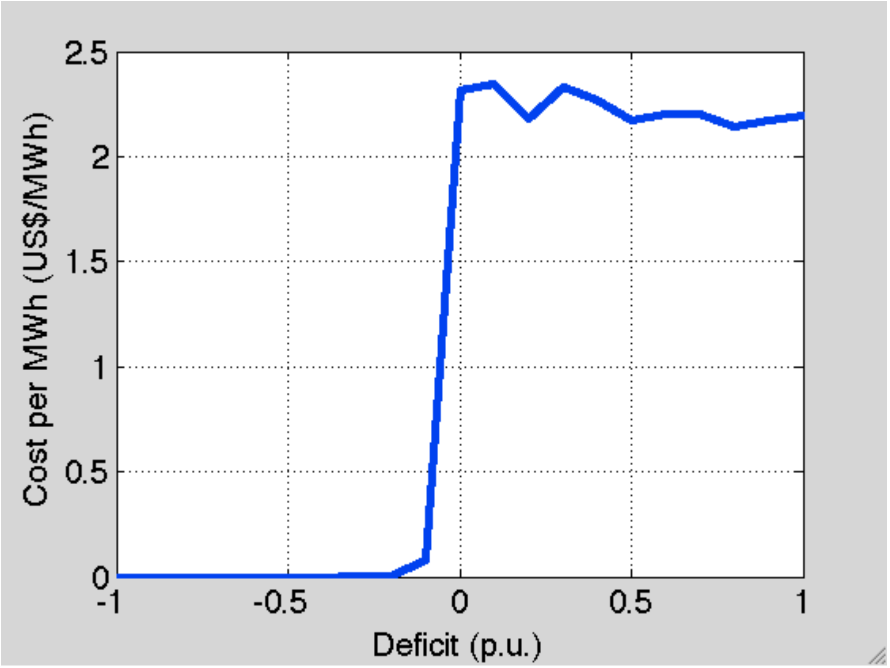


1X is orginal forecast error; 2X (3X) is twice (3 times) error

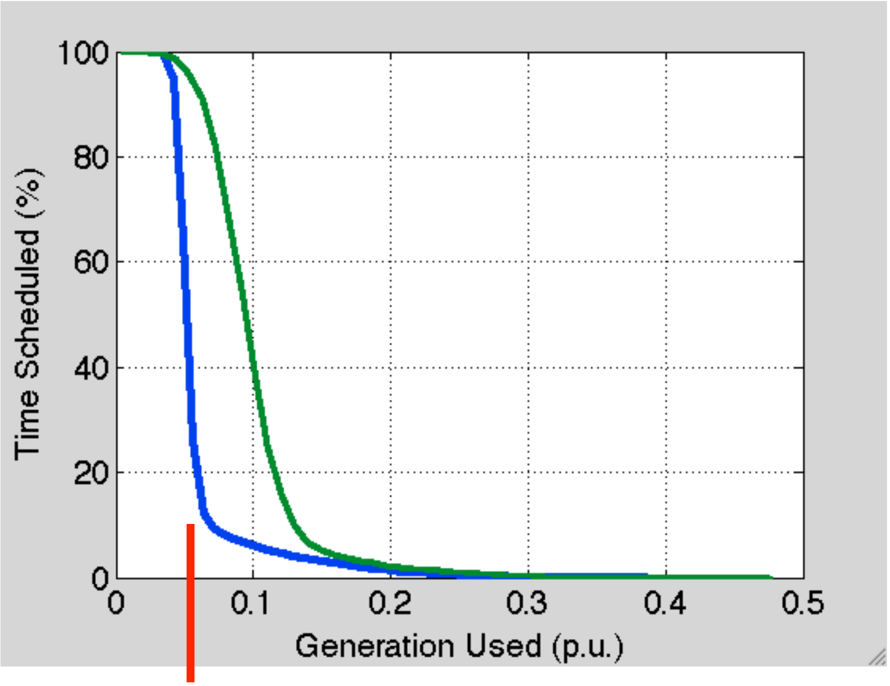
3-stage - 4-stage minimum cost per MWh (\$2.2 $\rightarrow$ \$4.5 $\rightarrow$ \$7.2)

Example C: additional energy purchased

1. 3-stages: 24-ahead \$52, 1-hr \$60, VOLL \$1000.
2. 4-stages: 24-ahead \$52, 1-hr \$60, 15-min \$72, VOLL \$1000



Reserve cost savings \$2.2/MWh



For $D = .04$:

3-stages buys 0.08 60% of time

4-stages buys 0.08 8% of time

Limitations

- No unit commitment
- No network constraints
- No ramp limits

Conclusion (1/2)

When VG penetration exceeds 20% there will be need for advanced dispatch procedures like RLD.

Current distinction of contingency, load-following, regulation reserve not useful in advanced dispatch. Reserves mitigate risk.

Current point forecasts will need to be replaced by probabilistic forecasts to make full use of information.

Large VG may displace generation. Coal power gross margin in Germany may collapse from 6.15 to 3.50 euros/MWh. This may be financially unsustainable.

Conclusion (2/2)

Wind is generation, not negative load. Reserve subsidy for wind may have to be reduced. RLD can help wind aggregators meet their reserve needs.

Better forecasts and less variability can be achieved by controlling demand to match VG.

Wind ramps are not accurately modeled as Gaussian processes. RLD permits non-Gaussian errors.

Achieving low LOLP with realistic (non-Gaussian, heavy-tailed) ramp forecast errors will require very large levels of reserves. There is a need for more general measures of risk.