Demand Response for Large Consumers of Electricity

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Introduction

- There are different flavours for demand side participation such as instigation of the microgrid.
- This talk will focus on tools to assist major energy users with consumption and reserve offer decisions.
- This talk is based on publications co-authored with G. Pritchard, B. Young, A. Downward, M. Ajos, M. Ferris, N. Cleland, M. Habibian, K. Abbaszadeh.

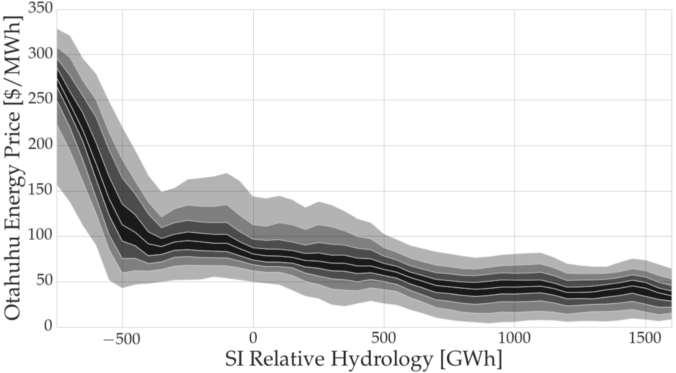
Why DR

- Good for the large consumers of electricity. Manufacturers (e.g. aluminium, steel), are under pressure to stay afloat. Need to optimize every aspect to survive economically. Electricity is a significant input for them (e.g. 20-40% cost of the aluminium production).
- Efficiency in the consumption helps electricity markets run more efficiently. By definition large consumers use a lot of electricity (15% of the nation's production for NZAS).
- Through DR we can accommodate renewable generation better.
- Given that the last generation units to produce are more likely to be polluting, DR facilitates "environmental efficiency".
- So we want demand to respond to price.

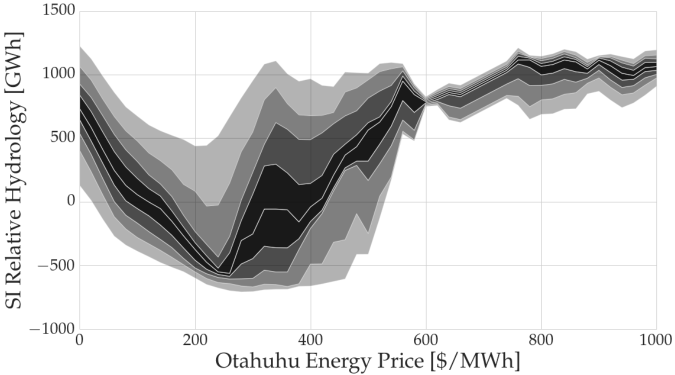
NZEM: What is the price?

- Roughly 55% – 65% of generation is from hydro, the rest from thermal and wind (no nuclear) and none can be imported.
- LMP: A uniform price auction determines the *nodal prices* and quantities to dispatch from each generator.
- In NZ, energy and reserve are co-optimized. This links the energy and reserve prices.
- The HVDC Inter-Island is New Zealand's only high voltage direct current (HVDC) system, and links the North and South Island grids together.

Lake level vs electricity prices (Jan 2008 to March 2014)



Examining a larger range



Top down analysis of price

Investigating the graphs above indicated that during periods of hydro plentifulness in SI, reserve needed to be procured in NI at high prices and this accounted for the correlation between high energy prices and full SI hydro lakes.

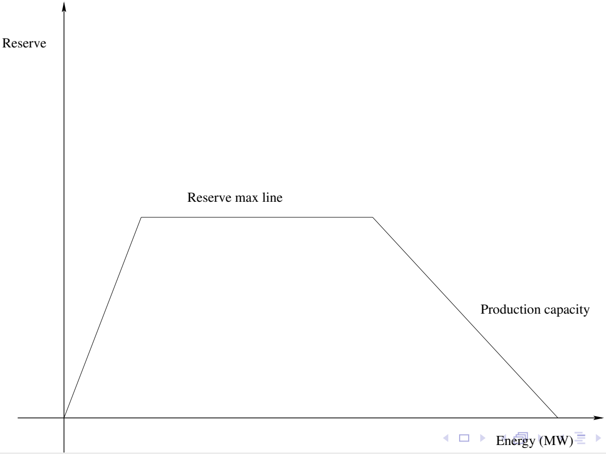
Bottom up: Simple reserve effects

- In the NZEM, to cover $N-1$ risk, we ensure that the largest source of electricity supply is covered by reserve.
- We do this in each of the islands.
- This implies that when the marginal generator is also the risk setter *procuring one more unit of energy would require procuring one more unit of reserve as well.*
- Let p_e denote the marginal offer price of energy and let p_r be the price of reserve. The *clearing price* of electricity is then

$$\pi = p_e + p_r.$$

Bath-tub effects

Energy and reserve are tied together by 3 linear constraints that constitute the "reverse bath-tub curve".



More complicated reserve effects

$$
\begin{aligned}
\min \quad & Ax_2 + Br & & (1)\\
\text{s/t} \quad & x_1 - f = 0 & [\lambda_1] \\
& x_2 + f = d & [\lambda_2] \\
& r - f \geq 0 & [\mu] \\
& r - kx_2 \leq 0 & [\kappa] \\
& x_1, x_2, r \geq 0 &
\end{aligned}
$$

Pricing effects

Consider the situation without the proportionality constraint, $r - kx_2 \leq 0$. If $B < A$ then $x_1 = r = d$ with total system cost of Bd. Otherwise $x_2 = d$ with a system cost of Ad. However, considering the proportionality constraint with $B < A$ we obtain.

$$\begin{aligned} r &= kx_2 \\ r &= f \\ r &= x_1 \\ x_2 + f &= d \end{aligned}$$

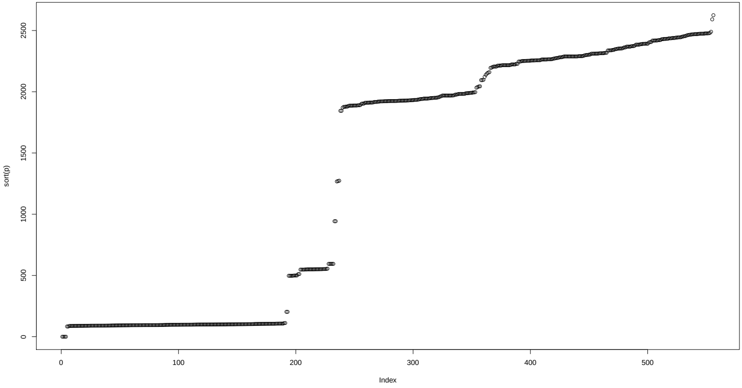
This renders the total system cost of

$$A\frac{d}{k+1} + B\frac{kd}{k+1}$$

and the final clearing price at node 2 is:

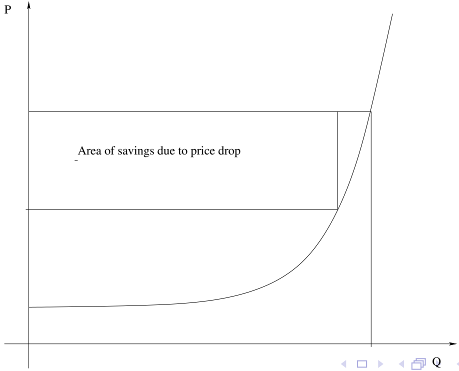
$$\lambda_2 = A + k\frac{B-A}{k+1}$$

Nodal prices for 2012 October 3 period TP19



Price maker models

- Some markets are imperfectly competitive (NZ, Singapore, etc).
- In these markets, it makes sense for a consumer to behave strategically.



A small experiment

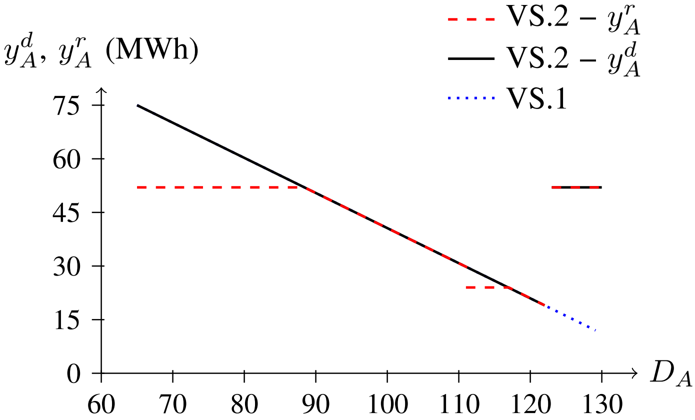


Fig. 3: Strategic Consumer Decision Variables

A small experiment continued

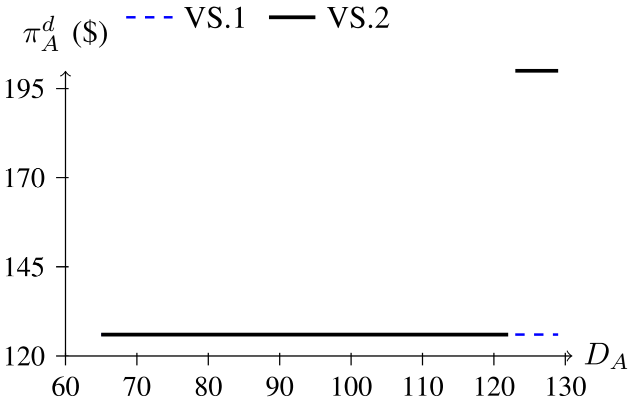


Fig. 4: Electricity Prices

Price maker continued

- We can formulate bi-level optimization problems to capture consumer profit maximization.
- These can be converted to MPECs (math programs with equilibrium constraints).
- Those can in turn be converted to integer optimization problems and (hopefully) solved.

ERDCOPF

$$
\begin{aligned}
\text{Max} \quad & \sum_{t_c \in \mathcal{T}_c} p^c_{t_c} x^c_{t_c} - \sum_{t_g \in \mathcal{T}_g} p^g_{t_g} x^g_{t_g} - \sum_{t_{rg} \in \mathcal{T}_{rg}} p^{rg}_{t_{rg}} x^{rg}_{t_{rg}} - \sum_{t_{rc} \in \mathcal{T}_{rc}} p^{rc}_{t_{rc}} x^{rc}_{t_{rc}} \\
\text{s.t.} \quad & \sum_{t_c \in \mathcal{T}^n_c} x^c_{t_c} + \sum_{i|ni \in \mathcal{A}} f_{ni} - \sum_{i|in \in \mathcal{A}} f_{in} = \sum_{t_g \in \mathcal{T}^n_g} x^g_{t_g} & [\pi^d_n] \\
& - \sum_{n \in \mathcal{N}_e} \sum_{z \in \{rc, rg\}} \sum_{t_z \in \mathcal{T}^n_z} x^z_{t_z} = -r_e & [\pi^r_e] \\
& \sum_{ij \in \mathcal{A}} L_{k,ij} f_{ij} = 0 & [\lambda_k] \\
& - K_{ij} \le f_{ij} \le K_{ij} & [\eta^+_{ij}, \eta^-_{ij}] \\
& 0 \le x^z_{t_z} \le q^z_{t_z} & [\nu^{z+}_{t_z}, \nu^{z-}_{t_z}] \\
& \sum_{t_{rc} \in \mathcal{T}^n_{rc}} x^{rc}_{t_{rc}} - \sum_{t_c \in \mathcal{T}'^n_c} x^c_{t_c} \le 0 & [\theta_n] \\
& \sum_{t_{rg} \in \mathcal{T}^n_{rg}} x^{rg}_{t_{rg}} \le B_n \sum_{t_g \in \mathcal{T}^n_g} x^g_{t_g} & [\phi_n] \\
& \sum_{t_{rg} \in \mathcal{T}^n_{rg}} x^{rg}_{t_{rg}} + \sum_{t_g \in \mathcal{T}^n_g} x^g_{t_g} \le W_n & [\phi'_n]
\end{aligned}
$$

Consumer's problem

$$[\text{PMP}]\ \text{Max} \quad \mathcal{U}(\sum_{n\in\mathcal{N}*} y_n^d) - (\sum_{n\in\mathcal{N}*} \pi_n^d y_n^d - \sum_{e\in\{N,S\}} \sum_{n\in\mathcal{N}_e^*} \pi_e^r y_n^r)$$

$$\text{s.t.} \quad 0 \leq y_n^d \leq C_n^d$$

$$0 \leq y_n^r \leq C_e^r$$

$$y_n^d - y_n^r \geq V_n$$

$$[\text{EROPF2}]\ \text{Max} \sum_{t_c\in\mathcal{T}_c} p_{t_c}^c x_{t_c}^c - \sum_{t_g\in\mathcal{T}_g} p_{t_g}^g x_{t_g}^g - \sum_{t_{rg}\in\mathcal{T}_{rg}} p_{t_{rg}}^{rg} x_{t_{rg}}^{rg} - \sum_{t_{rc}\in\mathcal{T}_{rc}} p_{t_{rc}}^{rc} x_{t_{rc}}^{rc}$$

$$\text{s.t.} \sum_{t_c\in\mathcal{T}_c^n} x_{t_c}^c + \sum_{i|ni\in\mathcal{A}} f_{ni} - \sum_{i|in\in\mathcal{A}} f_{in} = \sum_{t_g\in\mathcal{T}_g^n} x_{t_g}^g - y_n^d \qquad [\pi_n^d]$$

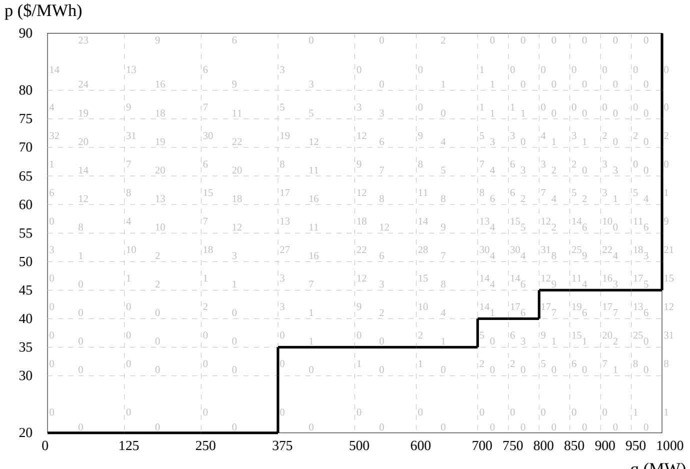
$$-\sum_{n\in\mathcal{N}_e} \sum_{z\in\{rc,rg\}} \sum_{t_z\in\mathcal{T}_z^n} x_{t_z}^z = \sum_{n\in\mathcal{N}_e} y_n^r - r_e \qquad [\pi_e^r]$$

remaining ERDCOPF equations

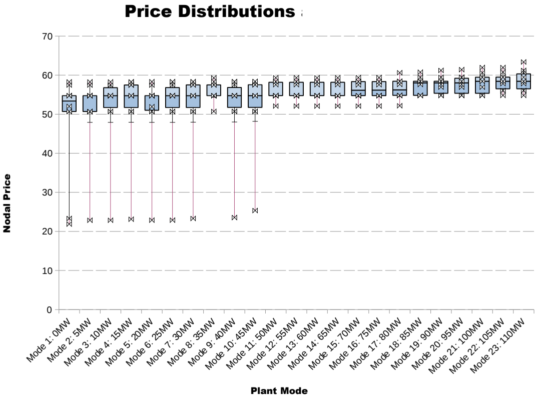
Simulation–optimization

- The bi-level optimization problem, in its full generality, stochastic and with demand bid function, as well as a reserve supply stack, was too hard to tackle at the start.
- We made some simplifications and approached this through simulation optimization.
    1. Fix the quantity of consumption at a level q.
    2. Trace out the *residual reserve demand* curves. Solve a dynamic program to find the optimal *reserve offer stack* coupled with q.
    3. With the optimal reserve stack, compute the distribution of prices we face when consuming q.

Step 2: Trace out rdcs and solve a SDP.



Compute the distribution of prices for each q



Change of paradigm

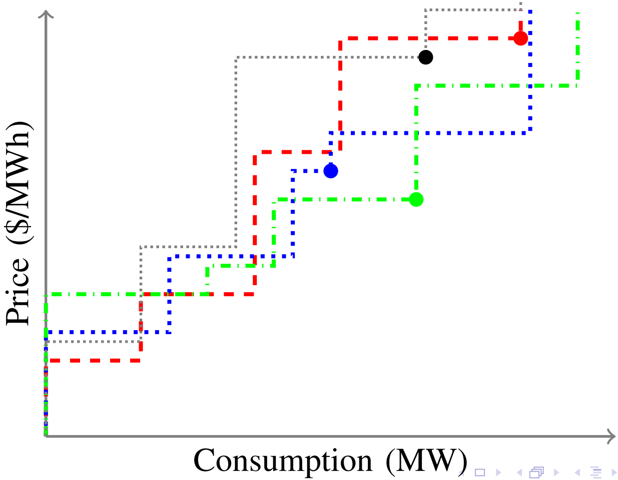
- This is good, but we need to fix on a single demand curve and a single supply function to submit to the market.
- (This is related to a question of auctions design: How much flexibility in bidding should be allowed.)
- So we reverted back to the MPEC.

Reformulating the MPEC as a MIP

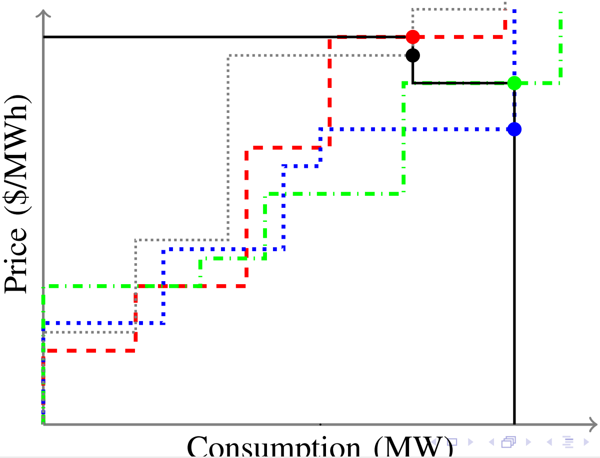
- The lower level problem is an LP, so it can be replaced by its KKT conditions.
- Following Fortuny-Amat and McCarl (JORS 1981), we can linearize the complementarity conditions using M (readily available as we are dealing with quantities and prices over an electricity market).
- The problem is hence transformed to one with a bilinear objective, linear constraints and binary variables.
- Once examined carefully, we can replace the bilinear objective terms with linear ones (thru the special OPF constraint forms).
- This approach is effective (in this deterministic case) for the full NZ model (over 250 nodes and about 500 arcs).

- We can generalize the MIP model to a stochastic version.
- However we need to build demand bid and reserve offers that are monotone.

Optimal points do not admit a monotone stack



Impose monotonicity constraints that couple scenarios



- We experimented with several MIP reformulations.
- Ultimately as the number of scenarios increased, the solution times grew exponentially.
- With 6 scenarios we ended up with 80,000 binary variables for the full NZEM.
- Even with 2 scenarios though, we saw significant $(40 - 70\%)$ improvement in the expected utility (policy is simulated "out of sample").

- Idea: write π_e, π_r as explicit functions of consumption and reserve offer quantities.
- This is essentially an efficient way to do a bivariate sensitivity analysis and can be performed separately and with a hot start for each scenario.
- Although this approach speeds up the solution time, when scenarios are similar the solution time still explodes. With different scenarios we build better solutions anyway, so we are in the process of quantifying this and getting to the bottom of "similarity" of stacks.

Multi-period optimization

- Build a price process and optimize the major user's production schedule over a time horizon.
- Immediate solution that comes to mind is an SDP.
- Capturing the price process, when we have a price maker, in addition to curse of dimensionality put us off this idea.
- Observation: The only link between the periods is the amount of consumption if the processes are simple enough.

- Total consumption level is G over a time horizon $\mathcal{T}$.

$$
\begin{aligned}
\text{[MIP]} \quad & \max \Pi(\mathbf{x}) = -\sum_{t\in\mathcal{T}} \mathcal{C}_t(\mathbf{x}_t) + \sum_{t\in\mathcal{T}} v x_t \\
& \text{s.t. } \mathbf{x}_t \in \mathcal{S}_t \qquad \forall t \in \mathcal{T} \\
& \sum_{t\in\mathcal{T}} x_t = G \qquad [\hat{u}]
\end{aligned}
$$

- If we could price the total consumption constraint, the problem could be decomposed over time periods.

Decomposition

- Choose an arbitrary u and define $[\text{U-MIP}]_u$ as the problem with the total consumption constraint removed, and instead valued in the objective, with multiplier u.

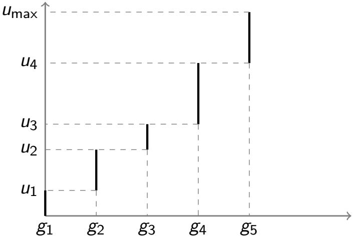
$$[\text{U-MIP}]_u \quad \max\; U(\mathbf{x}) = -\sum_{t\in\mathcal{T}} \mathcal{C}_t(\mathbf{x}_t) + \sum_{t\in\mathcal{T}} u x_t - Gu$$
$$\text{s.t. } \mathbf{x}_t \in \mathcal{S}_t \qquad \forall t \in \mathcal{T}$$

- (Lagrangian sufficiency) if $\sum_{t\in\mathcal{T}} x_t^* = G$ then we have hit the optimal solution for the original problem.

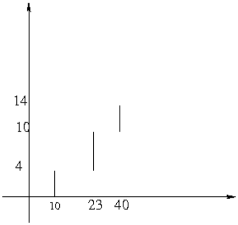
Decomposition

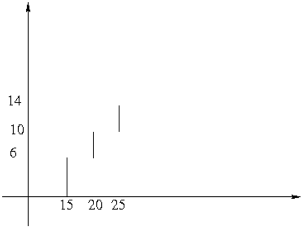
- Choose different *u*s, solve the problem and see we hit the right G.
- (This idea was inspired by Scott and Read 1996, who used demand curves to dispatch hydro.)
- For each individual period, we can eke out information through sensitivity analysis.

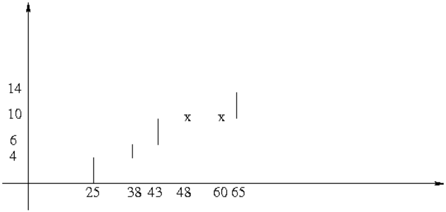
the figure below is for a single time period, but now need to combine these.



Example: Aggregating across 2 time periods







Observations

- The aggregation is reminiscent of offer stack aggregation.
- If the desired G appears in the aggregated UC diagram then we have an optimal solution.
- If not, there are rounding heuristics and one can also always solve:

$$
\begin{aligned}
\text{[HEU]} \quad & \min \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}_t} u_t^i x_t^i & \\
& \text{s.t.} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}_t} x_t^i = G & [\hat{u}] \\
& 0 \le x_t^i \le q_t^i - q_{t-1}^i & \forall i \in \mathcal{I}_t, \forall t \in \mathcal{T}
\end{aligned}
$$

Stochastic version

- The utility curves are the essence here.
- Mahbube has extended these for a stochastic version of the problem where we combine curves for scenarios into an expected utility curve.
- This enables us to adapt a stochastic dynamic approach.

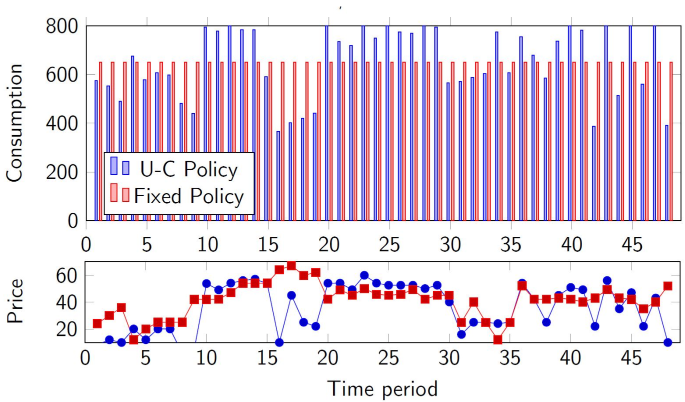
Case Study

Out-of-sample Optimization

- We implemented this approach for a large consumer of electricity in South Island.
- In order to simulate out of sample scenarios we used independent multi-variant normally distributed noise.
- We simulated our policy for 50 sample paths for a week long time horizon.

	Average cost per TP
U-C Policy	20705
Fixed Policy	23166

Case Study


800
600
400
200
0
Consumption
U-C Policy
Fixed Policy
0
5
10
15
20
25
30
35
40
45
60
40
20
Price
Time period

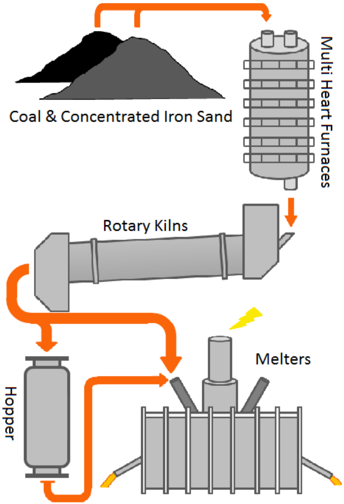
More complex operations

- In our (simplified version of the) aluminium production the only information linking the periods was consumption.
- The steel mill's operations are much more intricate.
- The type of flexibility available is also different.

Iron making

- If the electricity prices are high, kilns' output can be stored in the hopper instead of being processed in the melters.
- Storing RPCC in the hopper leads to changes in chemical properties of the RPCC in different levels of the hopper known as the "segregation effect".
- These changes amount to low levels of carbon content in the RPCC as material is retrieved from the bottom of the hopper and high carbon content as we retrieve the last of the stored material.
- Lower carbon implies the "slag" gets too close to the wall of the melter, but the high carbon content makes the feed too close to the electrodes and tends to "choke" the process.

Iron making


Coal & Concentrated Iron Sand
Multi Heart Furnaces
Rotary Kilns
Melters
Hopper

Solution approach

- All this put together points to a SP or SDP solution approach (we are working on both of these models).
- These however require a price process for electricity.
- Alan Ansell is looking at a machine learning time series for electricity prices (TS-FRESH developed by Andreas Kempa-Leihr and colleagues).

Grand plan

- Gain insight to industrial demand response.
- Develop tools that can be customized to different industries and used to obtain DR recommendations.
- Make this available NZ wide.

Chewing the fat

As this is work in progress any comments or questions are most welcomed?