Modelling distributed hydrogen as demand response

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Overview

- EPOC is a research partner in HINT project.
- Tony Downward was leading this project but has moved from the University of Auckland to join Contact Energy.
- Associate Professor Andrea Raith has joined the project in his place.
- Andrea is an expert in transportation modelling, so we are focusing research on the use of H2 as a transport fuel in a distributed production mode.
- Flexible production of H2 using wholesale electricity gives a demand response that will determine prices for reservoir models (JADE).
- This talk gives update of our modelling of demand response for H2.

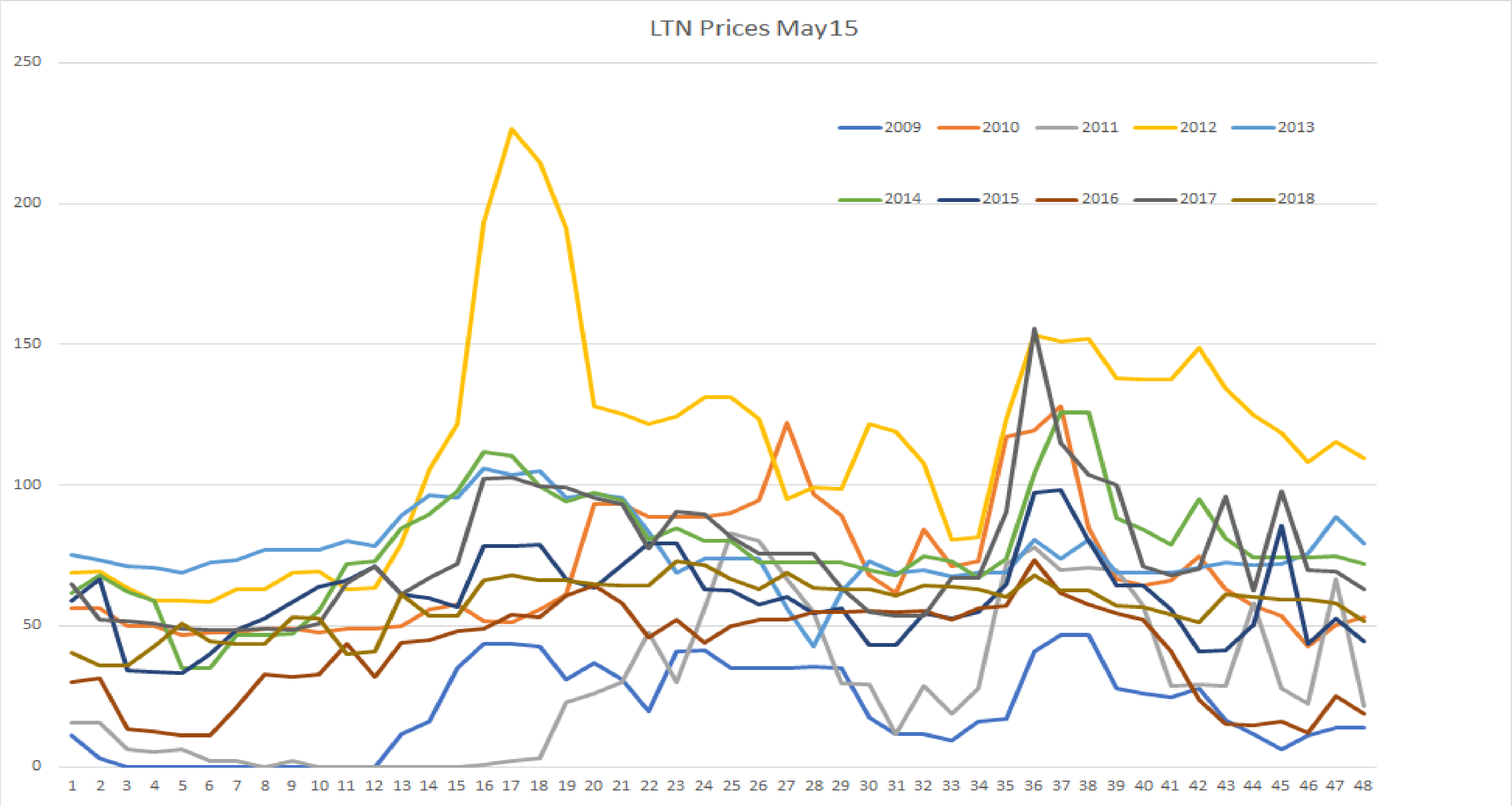
Peak shaving without storage

- Assume electricity prices from normal hydrology.
- Wholesale price in hour h is $p(h)$ NZD per MWh.
- Conversion of electricity to H2 is η MWh/kg.
- Electrolyser capacity L MW with cost \$$c$ per MW per day.
- Marginal value of H2 is $\pi(L)$ NZD per kg (decreasing with L).
- Rent from electrolyser (\$/h) in hour h is $R(h) = (\pi(L) / \eta - p(h))L$
- Shutdown electrolyser in h when $R(h) < 0$.
- Run electrolyser for h in H when $R(h) > 0$.
- Optimal capacity L when $(\pi(L) / \eta - p(h))|H|=c$

Peak shaving with storage

- Assume electricity prices from normal hydrology.
- Wholesale price in hour *h* is *p(h)* NZD per MWh.
- Conversion of electricity to H_2 is η MWh/Kg.
- Amount of hydrogen stored is *x* kg.
- Marginal value of H_2 in stock is $\pi(x,h)$ NZD per kg.
- Shutdown electrolyser when $p(h)\,\eta > \pi(x,h)$.
- $\pi(x,h)$ computed using dynamic programming (we use SDDP.jl).
- Assumes stagewise independent or Markov model for price *p(h)*.
- Model is trained based on this assumption.

May 15 example



SDDP.jl solution

Machine-learning alternatives

- Train decision-rule policies on historical data.
- Examples are threshold policies, buy if observed price less than threshold.
- We assume threshold = a*average price from previous week and estimate optimal a.
- Compare simulation of policy with clairvoyant model assuming perfect foresight of historical data.

Machine learning examples

	Clairvoyant solution			Threshold policy		
year	cost	unmet demand	max storage	cost	unmet demand	max storage
2009	2172901.63	0.00	4756	2398855.79	0.00	11820
2010	3683167.35	0.00	14057	3729465.49	0.00	13478
2011	3214697.38	0.00	6040	3506318.77	0.00	12454
2012	4691654.66	0.00	5443	4778152.62	0.00	5382
2013	3764547.70	0.00	12820	4078273.35	0.00	15140
2014	4322556.54	0.00	4539	4743117.02	0.00	17515
2015	3966450.28	0.00	2303	4296283.44	0.00	11870
2016	3268436.22	0.00	2496	3306999.56	0.00	2686
2017	4273365.13	0.00	6553	4429502.02	0.00	8005
2018	5099965.57	9290.94	29242	5316817.29	9071.03	29601

Dry winters

- Time scale now in weeks.
- Electricity prices can be high for weeks.
- Average wholesale price in week w is $p(w)$ NZD per MWh.
- Conversion of electricity to H2 is η MWh/kg.
- Amount of hydrogen stored is x kg.
- Marginal value of H2 in stock is $\pi(x,w)$ NZD per kg.
- Shutdown electrolyser for week w when $p(w)\,\eta > \pi(x,w)$.
- $\pi(x,w)$ computed using dynamic programming.

Capacity planning for a site

- Consider years $t = 0,1,2,\ldots$
- Assume probability distribution of electricity price in year t.
- Assume electrolyser capacity L MW and H2 storage S kg.
- Assume capital costs $C(L)$, $K(S)$, and discount rate ρ.
- Let $V_t(L,S)$ be expected cost of meeting H2 demand in year t.
- Choose L and S to

$$\text{minimize } C(L) + K(S) + \Sigma_t \; \rho^t V_t(L,S)$$

- This can be solved using SDDP.jl.

Linking with JADE

- JADE models demand response using a demand curve.
- Load reduction increases in tranches with increasing prices.
- SDDP H2 load reduction depends on $\pi(x,w)$ where x = H2 storage.
- Decision rule threshold price p depends on last week average electricity price, which is decreasing with national hydro storage s.
- Shortage cost = $p(s)y(s)$ where $p(s)$ decreasing $y(s)$ decreasing.

System effects and competitive equilibrium

- Consider years *t* = *0,1,2,…*
- Assume probability distribution of electricity price in year *t*.
- Assume demand for H2 in year *t*.
- Yields optimal investments in H2 facilities throughout NZ.
- Each facility has an optimal policy of shutting down when seeing high electricity prices.
- This demand response produces new electricity prices e.g. from JADE hydrothermal model.
- Equilibrium when JADE prices “match” assumed prices.

The End

The value of demand response

- Electrolyser demand can be reduced when prices are high.
- Equivalent to running peaking plant in dispatch models.
- Benefits
  - Peak shaving
  - Dry winter firming
- Drawbacks
  - Capacity utilization < 100%
  - Temptation to run at full capacity once investment made
  - But never optimal to run when marginal value of H2 exceeds production cost
- Storage
  - Enables price arbitrage while meeting demand