Modelling 100 percent renewable electricity

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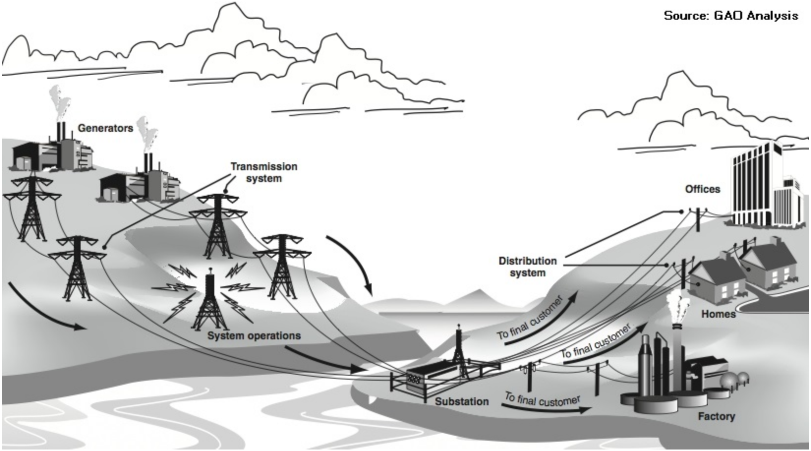
Engineering, Economics and Environment



- Determine generators' output to reliably meet the load
- Power flows cannot exceed lines' transfer capacity
- Tradeoff: Impose environmental constraints/regulations

New Zealand: How to implement Jacinda's deal

3. Request the Climate Commission to plan the transition to 100% renewable electricity by 2035 (which includes geothermal) in a normal hydrological year.

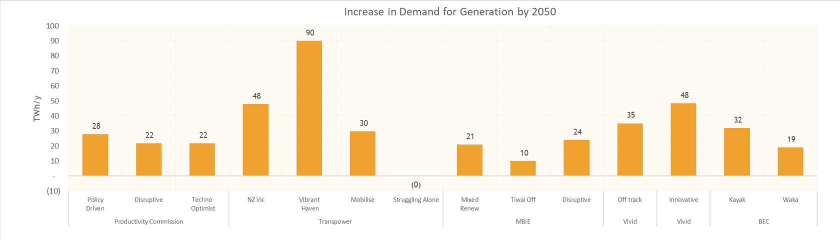
    a. Solar panels on schools will be investigated as part of this goal.

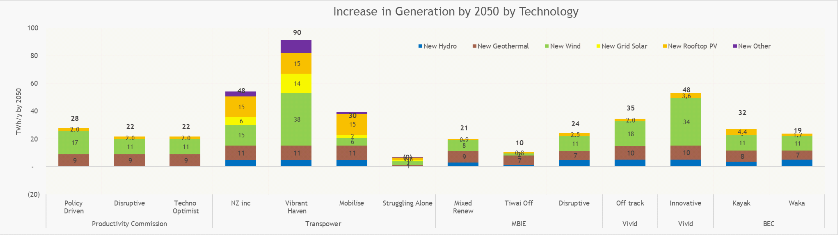
4. Stimulate up to $1 billion of new investment in low carbon industries by 2020, kick-started by a Government-backed Green Investment Fund of $100 million.

Confidence and Supply Agreement between the New Zealand Labour Party and the Green Party of Aotearoa New Zealand 3

Confidence and Supply Agreement between Labour Party and Green Party, October 2017. (https://www.greens.org.nz/sites/default/files)

Data uncertainty: multiple futures (ω)

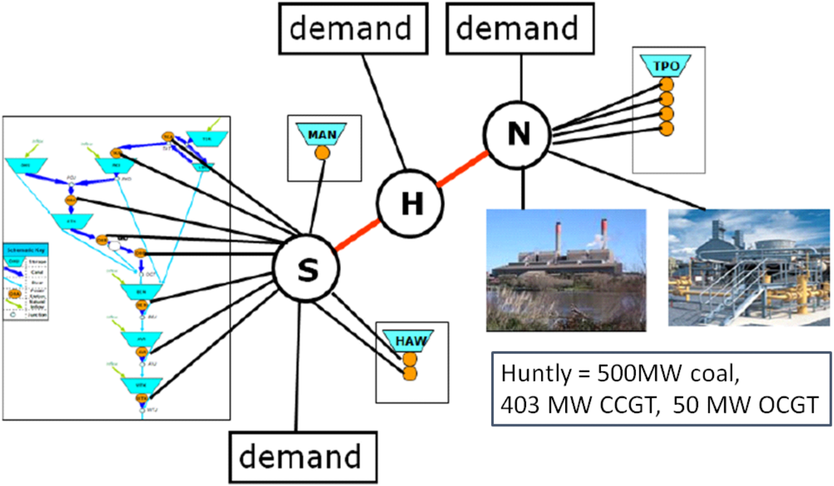




14 scenarios (ω) for electricity demand and generation mix in 2050.
There are 14 different optimal plans: which to select, if any?

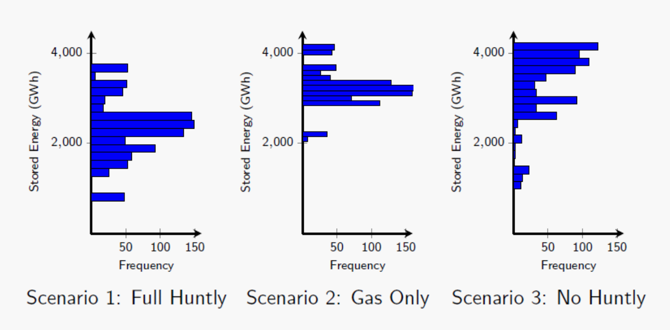
What does fully renewable in electricity mean?

- Permanently shutdown all thermal plants?
- Control GHG emissions from electricity generation?



Closing plants often increases average emissions (Fulton)

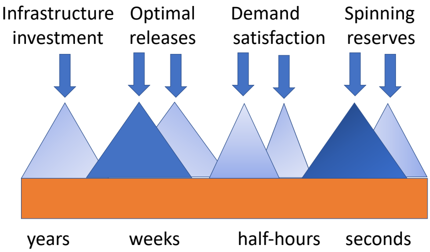
- Hydro can act as a giant battery
- Simulation runs: Reduce plant capacity, store more water "in case of dry winter":



- With low nonrenewable plant capacity, can't wait till last minute and reservoir levels in summer need to be close to full just in case. Tradeoff: Burning fuel to achieve this increases emissions.

Uncertainty is experienced at different time scales

- Demand growth, technology change, capital costs are long-term uncertainties (years)
- Seasonal inflows to hydroelectric reservoirs are medium-term uncertainties (weeks)
- Levels of wind and solar generation are short-term uncertainties (half hours)
- Very short term effects from random variation in renewables and plant failures (seconds)



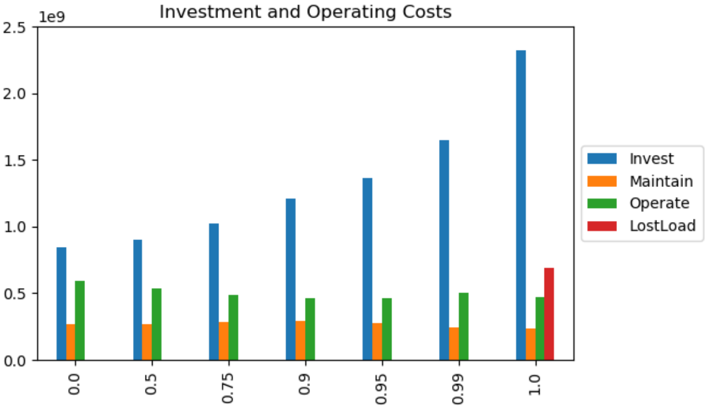
- Tradeoff: Uncertainty, cost and operability, regulations, security/robustness
- Needs modelling at finer time scales

Simplified two-stage stochastic optimization model

- Capacity decisions are z at cost $K(z)$
- Operating decisions are: generation y at cost $C(y)$, loadshedding q at cost Vq.
- Random demand is $d(\omega)$.
- Minimize capital cost plus expected operating cost:

$$
\begin{array}{llrcl}
\text{P:} & \displaystyle\min_{z,y,q\in X} & K(z) & + & \mathbb{E}_\omega[C(y(\omega)) + Vq(\omega)] \\
& \text{s.t.} & y(\omega) & \leq & z, \\
& & y(\omega) + q(\omega) & \geq & d(\omega), \\
& & \color{red}{z_{\mathcal{N}}} & \leq & \color{red}{(1-\theta)z_{\mathcal{N}}(2017)}
\end{array}
$$

Costs as we impose tighter emission restrictions



- Markets based on marginal (operating) prices
- Tradeoff: Building more capacity costs more, but makes operations cheaper - how to recover the fixed cost investment
- Operational costs dominated (at 100% renewable) by load shedding

More realistic model

Plant k has current capacity U_k, expansion x_k at capital cost K_k per MW, maintenance cost L_k per MW, and operating cost C_k. Minimize fixed and expected variable costs. Here $t = 0, 1, 2, 3$, is a season and $w(t)$ is reservoir storage at end of season t.

$$
\begin{aligned}
\text{P:} \quad \min \psi &= \textstyle\sum_k (K_k x_k + L_k z_k) + \sum_t \mathbb{E}_\omega [Z(t,\omega)] \\
\text{s.t.} \quad Z(t,\omega) &= \textstyle\sum_b T(b) \left(\sum_k C_k y_k(t,\omega,b) + Vq(t,\omega,b)\right), \\
x_k &\leq u_k, \\
z_k &\leq x_k + U_k, \\
y_k(t,\omega,b) &\leq \mu_k(t,\omega,b) z_k, \\
\textstyle\sum_b T(b) y_k(t,\omega,b) &\leq \nu_k(t,\omega) \textstyle\sum_b T(b) z_k \; + w(t-1) - w(t), \\
q(t,\omega,b) &\leq d(t,\omega,b), \\
d(t,\omega,b) &\leq \textstyle\sum_k y_k(t,\omega,b) + q(t,\omega,b), \\
w(t) &\leq W, \\
y, q, w &\geq 0.
\end{aligned}
$$

Operating costs are random

Plant k has current capacity U_k, expansion x_k at capital cost K_k per MW, maintenance cost L_k per MW, and operating cost C_k. Transfer energy $w(t)$ from season t to season $t+1$. Minimize fixed and expected variable costs. Here $T(b)$ is the number of hours in load block b of annual load duration curve.

$$
\begin{array}{rrcl}
\text{P:} & \min \psi & = & \sum_k (K_k x_k + L_k z_k) + \sum_t \mathbb{E}_\omega [Z(t,\omega)] \\
\text{s.t.} & Z(t,\omega) & = & \sum_b T(b) \left(\sum_k C_k y_k(t,\omega,b) + Vq(t,\omega,b) \right), \\
& x_k & \leq & u_k, \\
& z_k & \leq & x_k + U_k, \\
& y_k(t,\omega,b) & \leq & \mu_k(t,\omega,b) z_k, \\
& \sum_b T(b) y_k(t,\omega,b) & \leq & \nu_k(t,\omega) \sum_b T(b) z_k + w(t-1) - w(t), \\
& q(t,\omega,b) & \leq & d(t,\omega,b), \\
& d(t,\omega,b) & \leq & \sum_k y_k(t,\omega,b) + q(t,\omega,b), \\
& w(t) & \leq & W, \\
& y, q, w & \geq & 0.
\end{array}
$$

Shedding load incurs VOLL penalties

Plant k has current capacity U_k, expansion x_k at capital cost K_k per MW, maintenance cost L_k per MW, and SRMC C_k. Transfer energy $w(t)$ from season t to season $t+1$. Minimize fixed and expected variable costs.

$$
\begin{array}{rrcl}
\text{P:} & \min \psi & = & \sum_k (K_k x_k + L_k z_k) + \sum_t \mathbb{E}_\omega [Z(t,\omega)] \\
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 & \sum_b T(b) y_k(t,\omega,b) & \leq & \nu_k(t,\omega) \sum_b T(b) z_k + w(t-1) - w(t), \\
 & q(t,\omega,b) & \leq & d(t,\omega,b), \\
 & d(t,\omega,b) & \leq & \sum_k y_k(t,\omega,b) + q(t,\omega,b), \\
 & w(t) & \leq & W, \\
 & y, q, w & \geq & 0.
\end{array}
$$

Capacity of wind and run-of-river is random in a season

Plant k has current capacity U_k, expansion x_k at capital cost K_k per MW, maintenance cost L_k per MW, and SRMC C_k. Minimize fixed and expected variable costs.

$$
\begin{array}{rcl}
\text{P:} \quad \min \psi & = & \sum_k (K_k x_k + L_k z_k) + \sum_t \mathbb{E}_\omega [Z(t,\omega)] \\
\text{s.t.} \quad Z(t,\omega) & = & \sum_b T(b) \left(\sum_k C_k y_k(t,\omega,b) + Vq(t,\omega,b) \right), \\
x_k & \leq & u_k, \\
z_k & \leq & x_k + U_k, \\
y_k(t,\omega,b) & \leq & \mu_k(t,\omega,b) z_k, \\
\sum_b T(b) y_k(t,\omega,b) & \leq & \nu_k(t,\omega) \sum_b T(b) z_k + w(t-1) - w(t), \\
q(t,\omega,b) & \leq & d(t,\omega,b), \\
d(t,\omega,b) & \leq & \sum_k y_k(t,\omega,b) + q(t,\omega,b), \\
w(t) & \leq & W, \\
y, q, w & \geq & 0.
\end{array}
$$

Energy input from reservoir inflows is random in a season

Plant k has current capacity U_k, expansion x_k at capital cost K_k per MW, maintenance cost L_k per MW, and SRMC C_k. Minimize fixed and expected variable costs.

$$
\begin{array}{rrcl}
\text{P:} & \min \psi & = & \sum_k (K_k x_k + L_k z_k) + \sum_t \mathbb{E}_\omega [Z(t,\omega)] \\
\text{s.t.} & Z(t,\omega) & = & \sum_b T(b) \left(\sum_k C_k y_k(t,\omega,b) + Vq(t,\omega,b)\right), \\
 & x_k & \leq & u_k, \\
 & z_k & \leq & x_k + U_k, \\
 & y_k(t,\omega,b) & \leq & \mu_k(t,\omega,b) z_k, \\
 & \sum_b T(b) y_k(t,\omega,b) & \leq & \nu_k(t,\omega) \sum_b T(b) z_k + w(t-1) - w(t), \\
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 & d(t,\omega,b) & \leq & \sum_k y_k(t,\omega,b) + q(t,\omega,b), \\
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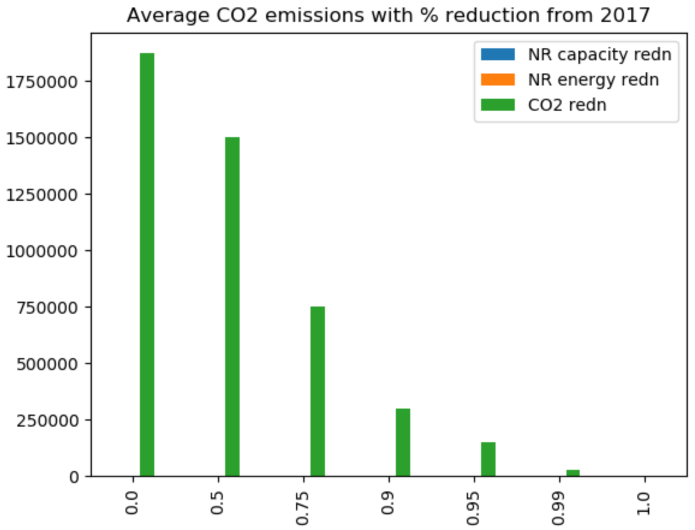
 & y, q, w & \geq & 0.
\end{array}
$$


Average CO2 emissions with % reduction from 2017
NR capacity redn
NR energy redn
CO2 redn
1750000
1500000
1250000
1000000
750000
500000
250000
0
0.0
0.5
0.75
0.9
0.95
0.99
1.0

Environmental constraints

Some capacity x_k, $k \in \mathcal{N}$, is "non renewable". Some generation $y_k(\omega)$, $k \in \mathcal{E}$ emits $\beta_k y_k(\omega)$ tonnes of CO2. For a choice of $\theta \in [0,1]$ constraint is either:

$$\mathbb{E}_\omega[\sum_{k\in\mathcal{E}} \beta_k y_k(\omega)] \leq (1-\theta)\mathbb{E}_\omega[\sum_{k\in\mathcal{E}} \beta_k y_k(\omega, 2017)],$$

(reduce CO2 emissions compared with 2017)

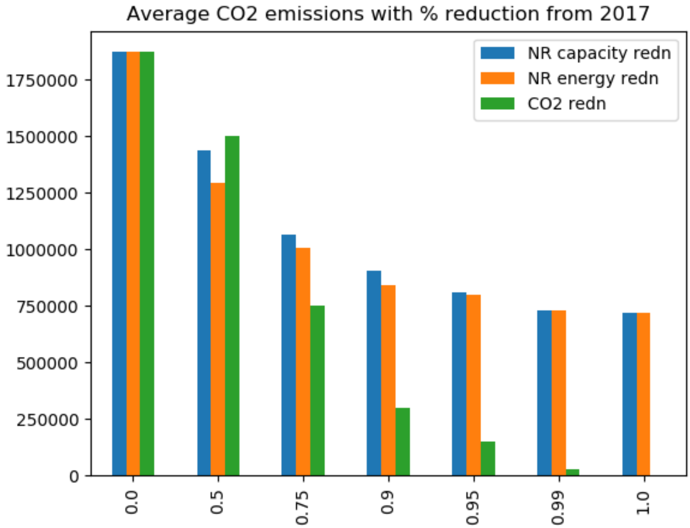
$$\sum_{k\in\mathcal{N}} z_k \leq (1-\theta) \sum_{k\in\mathcal{N}} z_k(2017),$$

(reduce non-renewable capacity compared with 2017)

$$\mathbb{E}_\omega[\sum_{k\in\mathcal{N}} y_k(\omega)] \leq (1-\theta)\mathbb{E}_\omega[\sum_{k\in\mathcal{N}} y_k(\omega, 2017)],$$

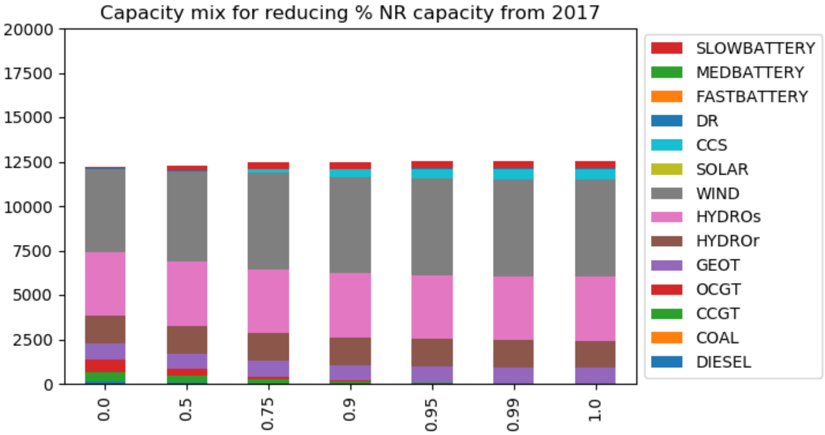
(reduce non-renewable generation compared with 2017)

Could impose constraints almost surely instead of in expectation or with risk measure (small impact)



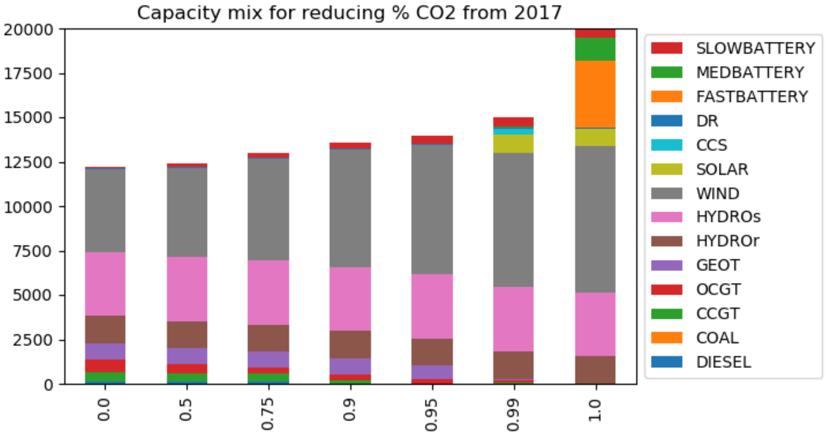
Since (renewable) geothermal and CCS emit some CO2 100% renewable yields modest reductions in CO2 emissions.

Technology choices as θ increases (NR capacity redn)



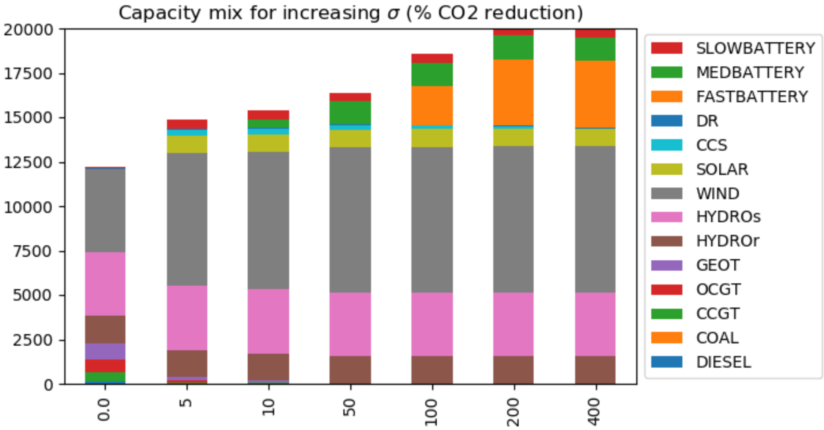
- Use geothermal, CCS, wind, batteries
- Fairly constant capacity

Technology choices as θ increases (% CO2 redn)



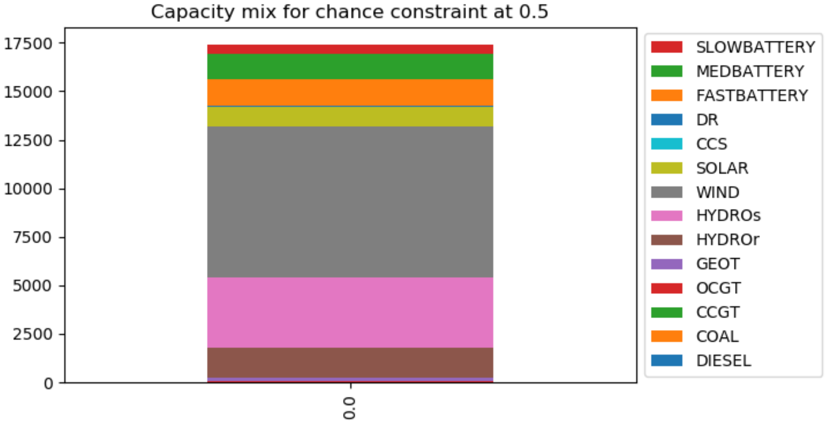
- Rich portfolio of renewable technologies used
- More capacity needed as more uncertain generation

Technology choices as carbon price ($ per MW) increases



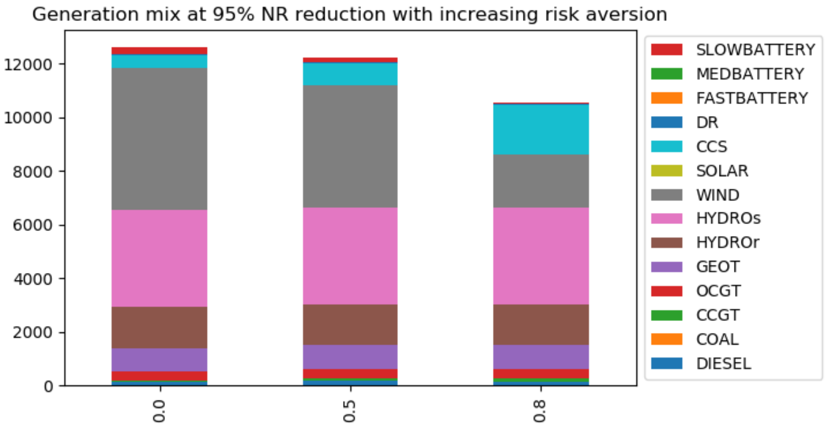
Technology choices (chance constraints)

Force zero emissions in at least 50% of years (normal hydrology)

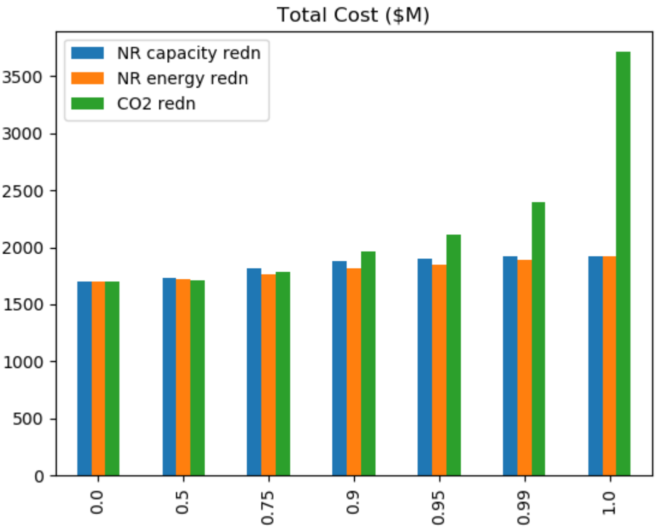


Emissions increase by 60%, cost increases by 20% over 99% renewable case

Risk-averse solutions for 95% NR energy reduction

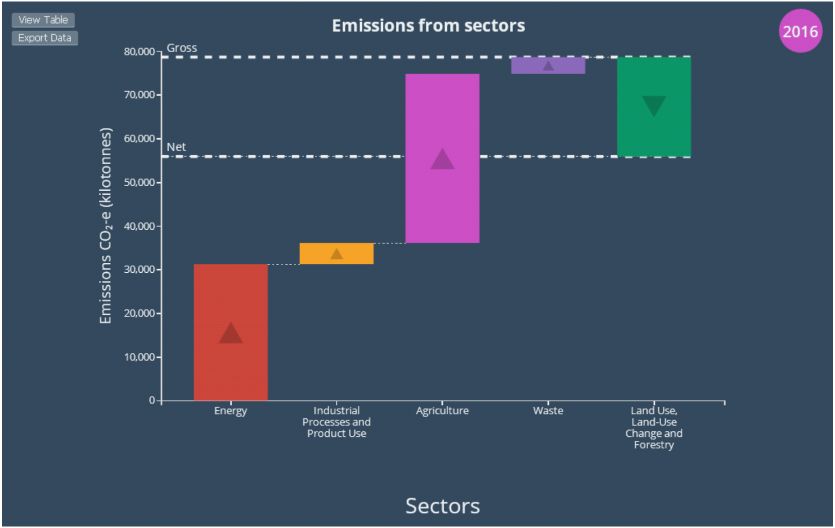


- Risk aversion modelled using $(1-\lambda)E[Z] + \lambda \text{AVaR}_{0.90}(Z)$, for $\lambda = 0, 0.5, 0.8$
- Replace wind/battery with CCS



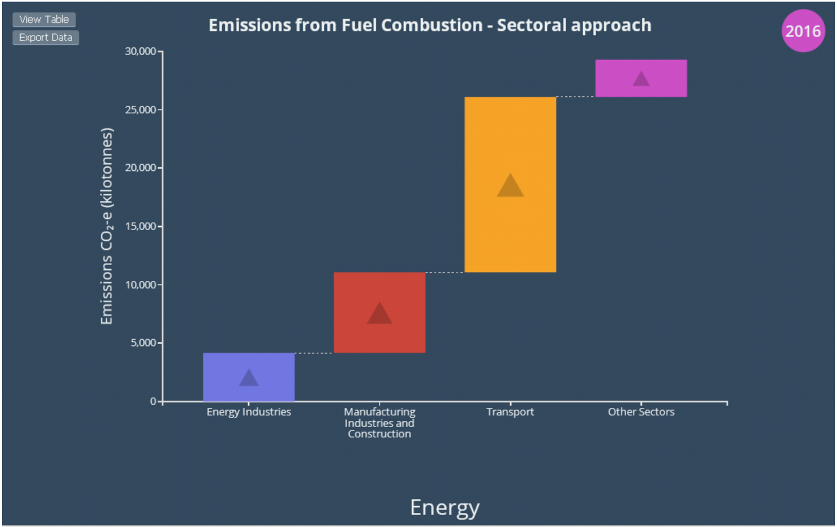
Cost of actually reaching zero CO2 emissions (without geothermal or CCS) increases as we approach the limit.

New Zealand greenhouse gas emissions



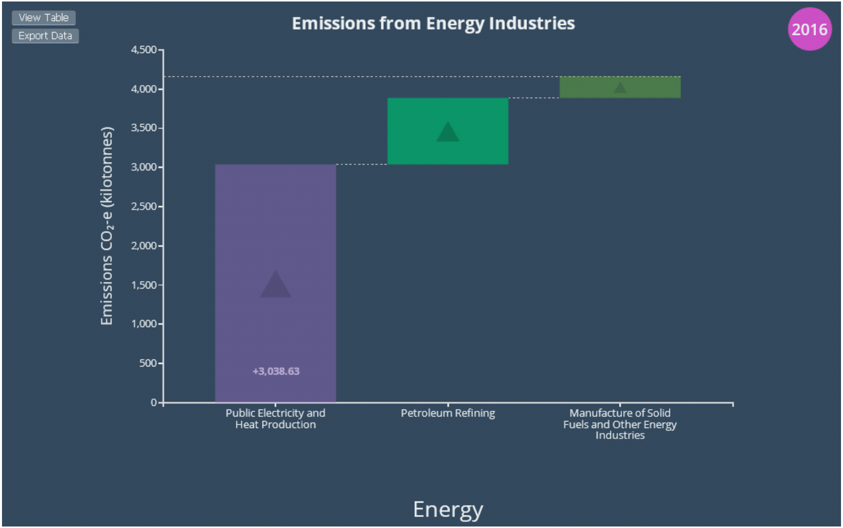
Total GHG emissions in 2016 were 80 M t CO2 equivalent.

New Zealand greenhouse gas emissions



Total CO2 emissions in 2016 were 30 M t.

New Zealand greenhouse gas emissions



Total CO2 emissions from electricity in 2016 were 3 M t.

General equilibrium (with contracts/incentives)

Consumption d_k, energy y_j, flows f, prices π, σ

$$\begin{aligned}
\text{Consumers} \quad & \max_{d_k \in \mathcal{C}} \text{utility}(d_k) - T_C(\sigma, d, f, y) - \pi^T d_k \\
\text{Generators} \quad & \max_{(y_j) \in \mathcal{G}} \text{profit}(y_j, \pi) - T_G(\sigma, d, f, y) \\
\text{Transmission} \quad & \min_{f \in \mathcal{F}} \text{congestion rates}(f, \pi)
\end{aligned}$$

Market clearing

$$0 \leq \pi \perp \sum_j y_j - \sum_k d_k - \mathcal{A}f \geq 0$$

$$0 \leq \sigma \perp E - \sum_j \mathcal{E}_j(y_j) \geq 0$$

Conclusions

- 100% renewable electricity system has several interpretations with different implications.
- Policy should choose the objective function not the action: e.g. reducing thermal capacity ceteris paribus can increase average emissions.
- Uncertainty in the model makes a difference.
- Electricity system has uncertainties at many time scales. Can include these in a single model with some approximations.
- If geothermal and CCS are renewable then 100% renewable is feasible, but emission reduction is modest.
- 100% emission reduction in NZ electricity is needlessly expensive given proportion of electricity emissions.
- Next steps: A multistage model, and its competitive equilibrium counterpart.

The Te Apiti Wind Farm, Manawatu, New Zealand. Image credits: Jondaar_1 / Flickr.

A mathematical modelling approach to planning

- Build and solve a social plannning model that optimizes electricity capacity investment with constraints on CO_2 emissions.
- Social planning solution should be stochastic: i.e. account for future uncertainty
- Social planning solution should be risk-averse: because the industry is.
- Approximate the outcomes of the social plan by a competitive equilibrium with risk-averse investors.
- Compensate for market failures from imperfect competition or incomplete markets.