Modelling 100 percent renewable electricity

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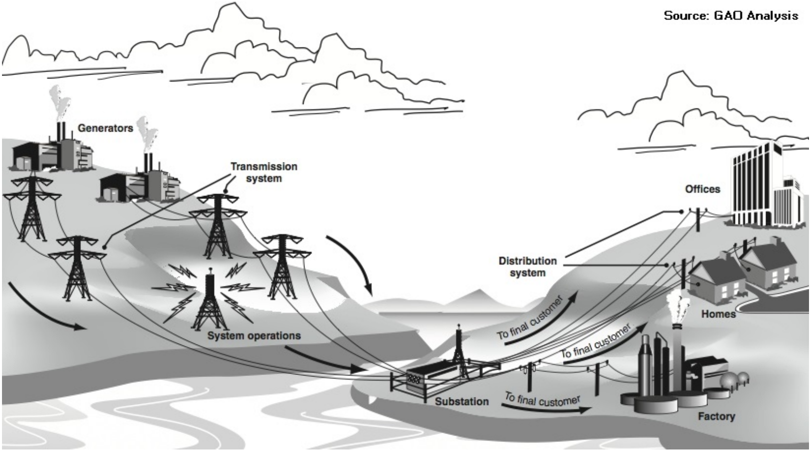
Engineering, Economics and Environment



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

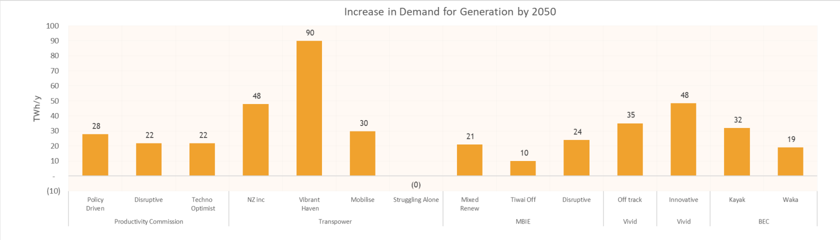
New Zealand: How to implement Jacinda's deal

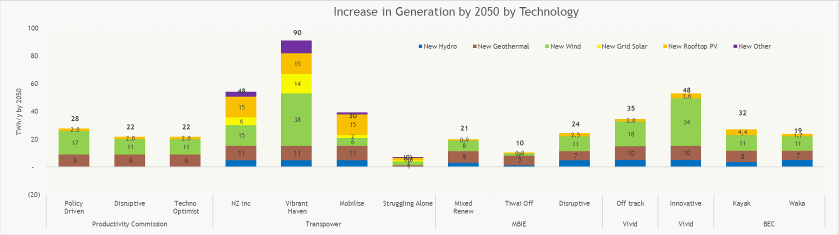
3. Request the Climate Commission to plan the transition to 100% renewable electricity by 2035 (which includes geothermal) in a normal hydrological year.
    a. Solar panels on schools will be investigated as part of this goal.
4. Stimulate up to $1 billion of new investment in low carbon industries 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)

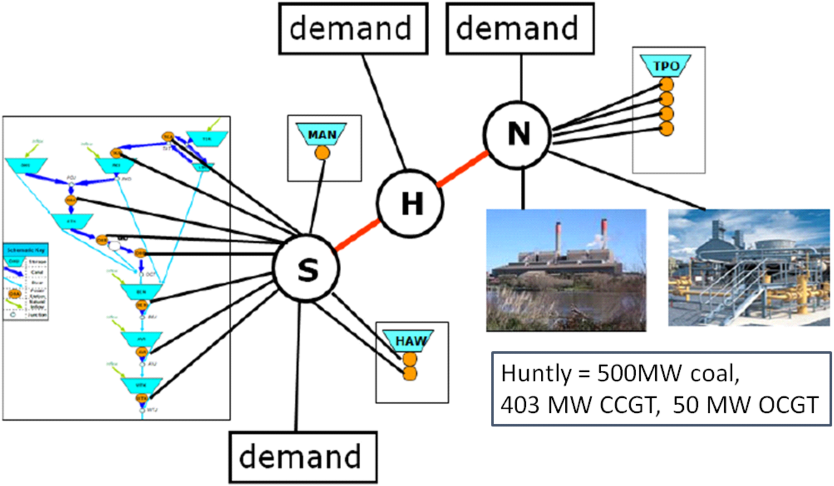




14 scenarios (ω) for electricity demand and generation mix in 2050.
There are 14 different optimal plans: which to select, if any?

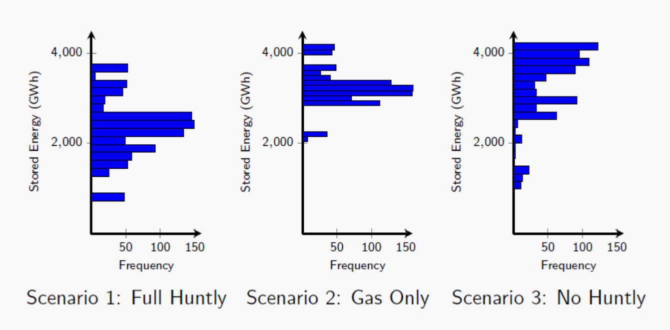
What does fully renewable in electricity mean?

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



Closing plants often increases average emissions (Fulton)

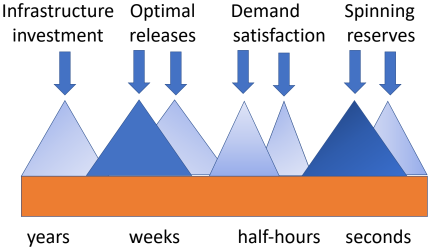
- Hydro can act as a giant battery
- Simulation runs: Reduce plant capacity, store more water "in case of dry winter":



- 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)



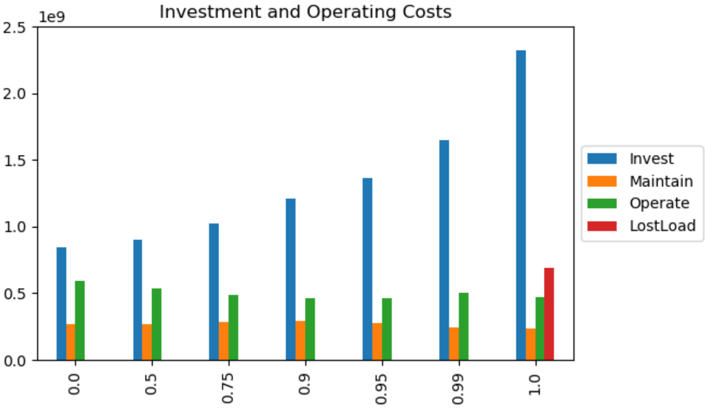
- Tradeoff: Uncertainty, cost and operability, regulations, security/robustness
- Needs modelling at finer time scales

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:

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

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.

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

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.

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

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.

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

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.

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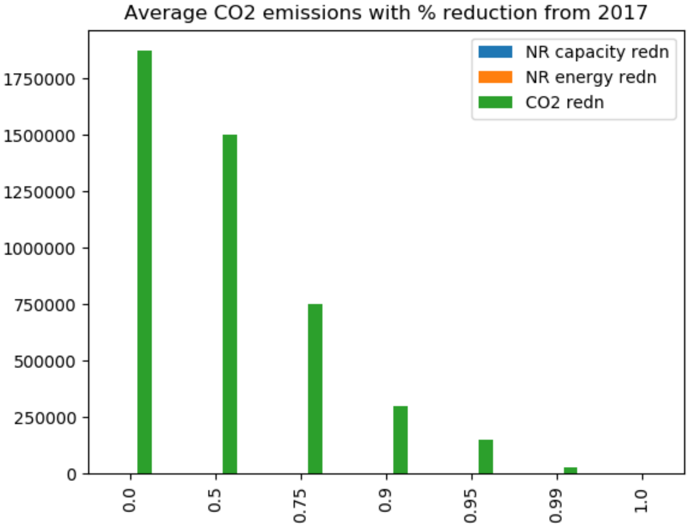
\end{array}
$$


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)

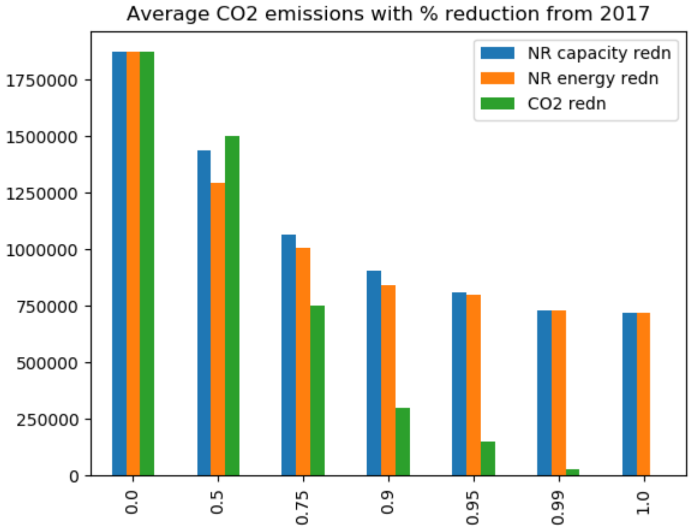
$$\sum_{k \in \mathcal{N}} z_k \leq (1-\theta) \sum_{k \in \mathcal{N}} z_k(2017),$$

(reduce non-renewable capacity compared with 2017)

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

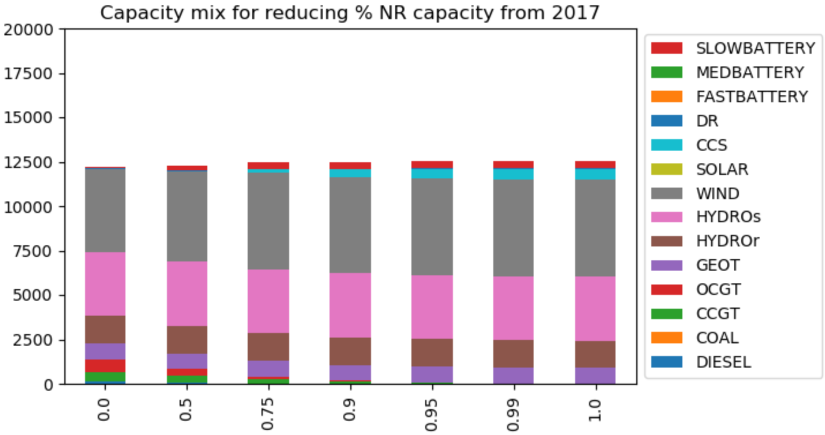
(reduce non-renewable generation compared with 2017)

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



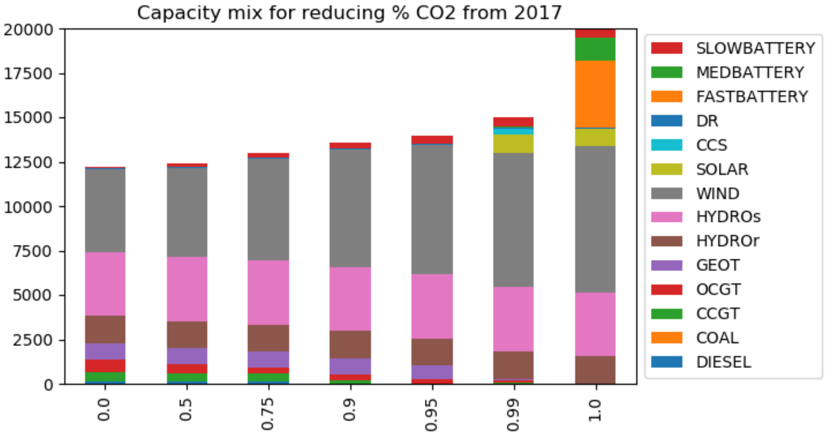
Since (renewable) geothermal and CCS emit some CO_2 100% renewable yields modest reductions in CO_2 emissions.

Technology choices as θ increases (NR capacity redn)



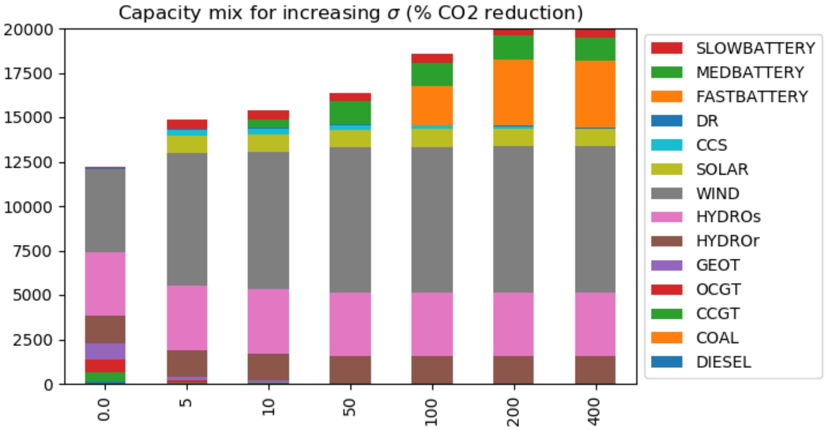
- Use geothermal, CCS, wind, batteries
- Fairly constant capacity

Technology choices as θ increases (% CO2 redn)



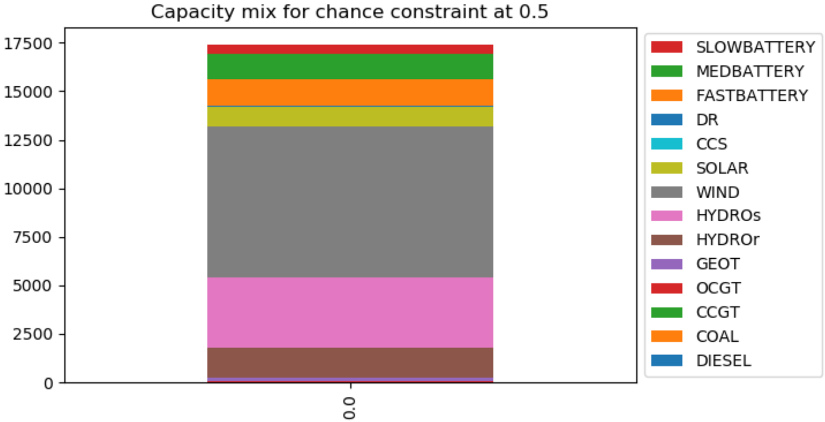
- Rich portfolio of renewable technologies used
- More capacity needed as more uncertain generation

Technology choices as carbon price ($ per MW) increases



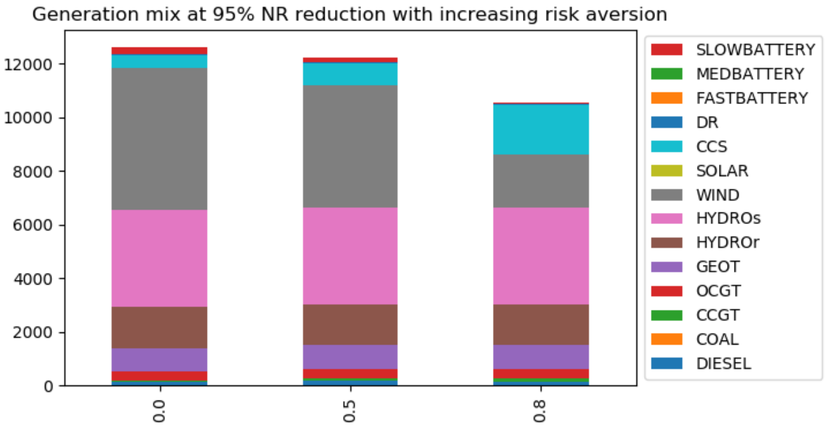
Technology choices (chance constraints)

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

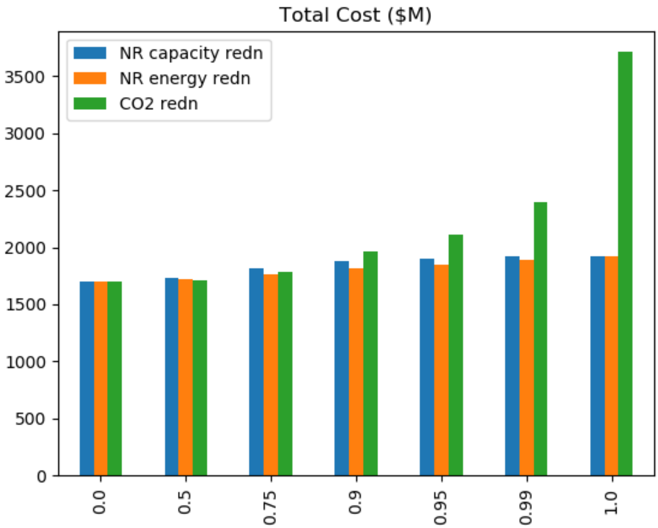


Emissions increase by 60%, cost increases by 20% over 99% renewable case

Risk-averse solutions for 95% NR energy reduction

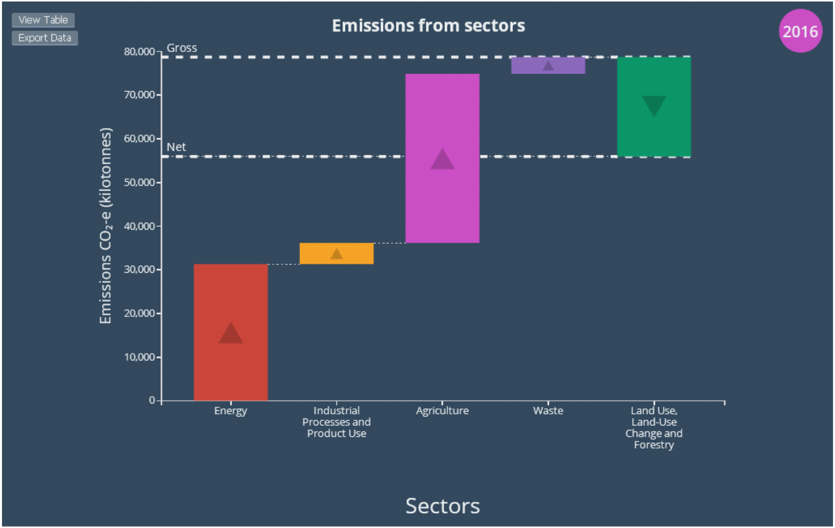


- Risk aversion modelled using $(1-\lambda)E[Z] + \lambda \mathrm{AVaR}_{0.90}(Z)$, for $\lambda = 0, 0.5, 0.8$
- Replace wind/battery with CCS



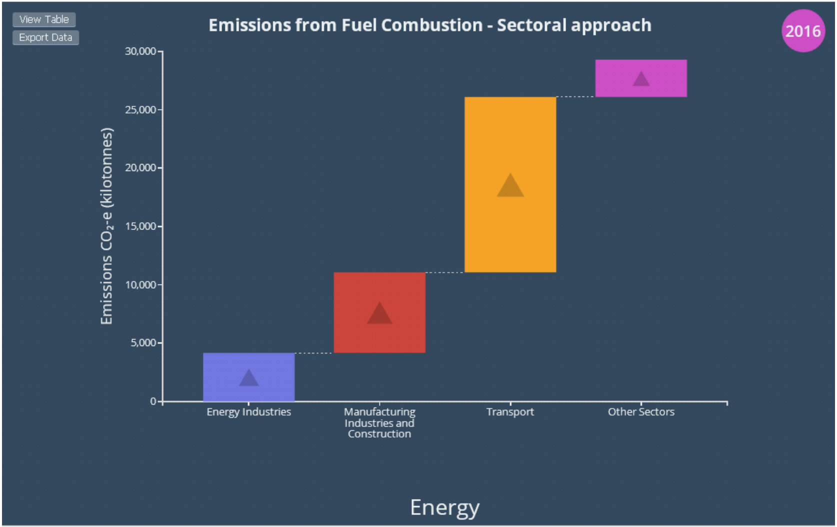
Cost of actually reaching zero CO_2 emissions (without geothermal or CCS) increases as we approach the limit.

New Zealand greenhouse gas emissions



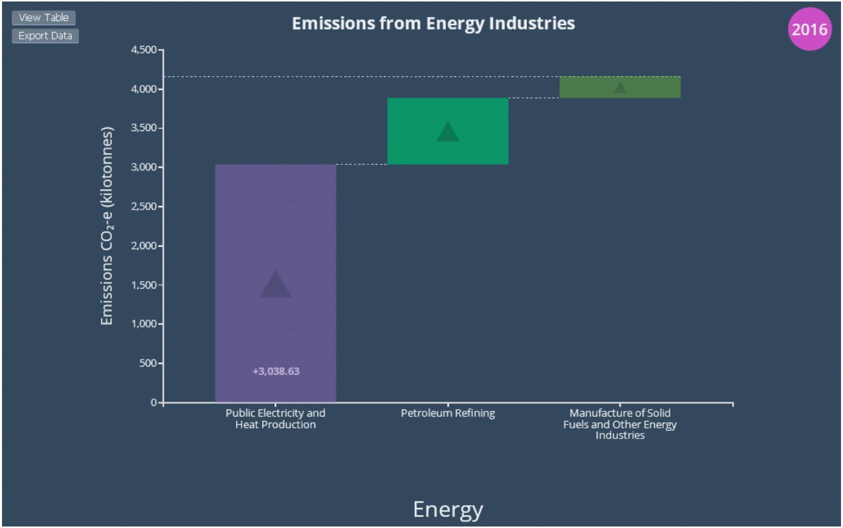
Total GHG emissions in 2016 were 80 M t CO2 equivalent.

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

$$0 \le \pi \perp \sum_j y_j - \sum_k d_k - \mathcal{A} f \ge 0$$

$$0 \le \sigma \perp E - \sum_j \mathcal{E}_j(y_j) \ge 0$$

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 CO2 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.