Computing the impact of changes to New Zealand's generation mix on hydro-reservoir management

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Outline

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Motivation

Huntly Coal Shutdown

- Since 2015 there have been several announcements about the shutdown of the remaining coal-power Rankine units at Huntly by 2018 and then 2022.
- There was subsequently an announcement in 2016 that one of the mothballed units could be recommissioned.
- The most recent announcement is that coal will no longer be used at Huntly after 2030.
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New Zealand's 100% renewable target

- In the longer term, New Zealand has a target of 100% renewables[2] for the electricity system.
- This will mean approximately 1400MW of thermal capacity will either be shutdown or lie dormant for more than 50% of years.
- We will not seek to tackle the long-run price signals necessary to invest in new renewables, while also maintaining backup thermal plant.
- We will model several scenarios to understand how hydro-storage management needs to adapt to these new generation mixes.

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Multistage stochastic programming

Solution techniques for multistage stochastic programming problems are an active area of research. However, many techniques are some extension of Benders decomposition.

For convex problems, *stochastic dual dynamic programming* (`SDDP`) is the most well known algorithm. However, in practice there are many other approximate algorithms that are often used.

Background

Traditional SDDP assumptions

The following assumptions are typical of traditional SDDP implementations.

- Finite number of stages, $t \in \{1, \ldots, T\}$, with a terminal cost-to-go.
- Stage-problem is a linear program.
- Optimal objective function of stage-problem is convex with respect to some state-vector x.
- Noise $\omega \in \Omega_t$ is discrete and stagewise independent.

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Hydro-thermal scheduling stage-problem

In stage t, we solve:

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\begin{array}{rll}
V_t\left(x_t, \omega\right) = \min\limits_{g_t, h_t, x_{t+1}} & c_t^\top g_t + \mathbb{E}_{\omega' \in \Omega_{t+1}}[V_{t+1}(x_{t+1}, \omega')] & \\
\text{s.t.} & x_{t+1} + h_t = x_t + \omega & \text{[reservoir balance]} \\
& e^\top g_t + e^\top h_t = d_t & \text{[demand balance]} \\
& g_t, h_t, x_{t+1} \geq 0, &
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where x_t is the incoming reservoir levels for stage t, x_t is the outgoing reservoir levels, and ω is the random inflows observed at the beginning of stage t. g_t and h_t are the thermal and hydro generation, respectively, in stage t.

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where x_t is the incoming reservoir levels for stage t, x_t is the outgoing reservoir levels, and ω is the random inflows observed at the beginning of stage t. g_t and h_t are the thermal and hydro generation, respectively, in stage t.

In stage T, we have some predefined function for $\mathcal{V}_{T+1}(x_{T+1})$; however, in all other stages, an approximation of $\mathcal{V}_t(x_{t+1})$ will be refined over the course of the algorithm.

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Infinite horizon stage-problem

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For stage T, we can set:

$$\mathcal{V}_{T+1}(x_{t+1}) = \rho V_1(x_{t+1}) \qquad \text{[discounted cost model]}$$

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Discrete Example

Details and assumptions

We wish to model the production from a single hydroelectric generator with a dedicated dam over a 1-hour period.

- The hydroelectric dam has a maximum storage level, X MWh.
- There is a turbine with a maximum power output, H MW.
- There are thermal generators offering at increasing marginal cost, $\$C_t'(g)$ /MWh.
- Any electricity produced is sold on the spot-market with a demand of d_t MW.
- The inflows, ω MWh, in each stage are uncertain, and occur (and are observed) at the beginning of each stage.

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The dynamic programming recursion can be written as follows:

$$\mathcal{V}_t(x) = \mathbb{E}_{\omega \in \Omega}\left[\min_{h \in \mathcal{H}}\{C_t(d_t - h) + \mathcal{V}_{t+1}(x - h + \omega)\}\right].$$

There are a discrete set of actions $h \in \mathcal{H}$, which must comply with various practical limits:

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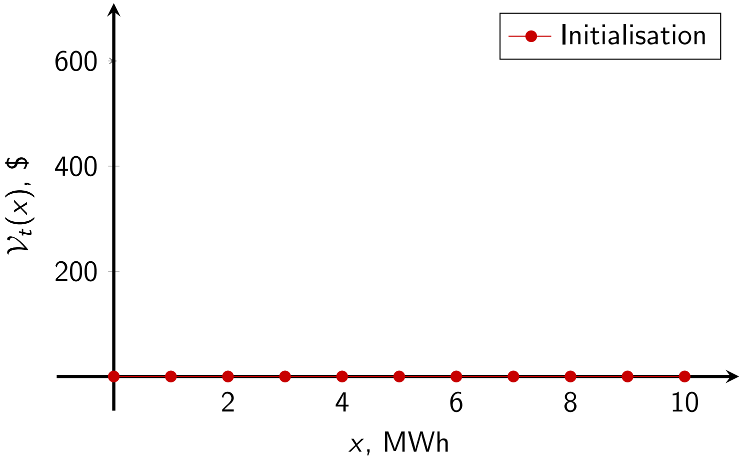

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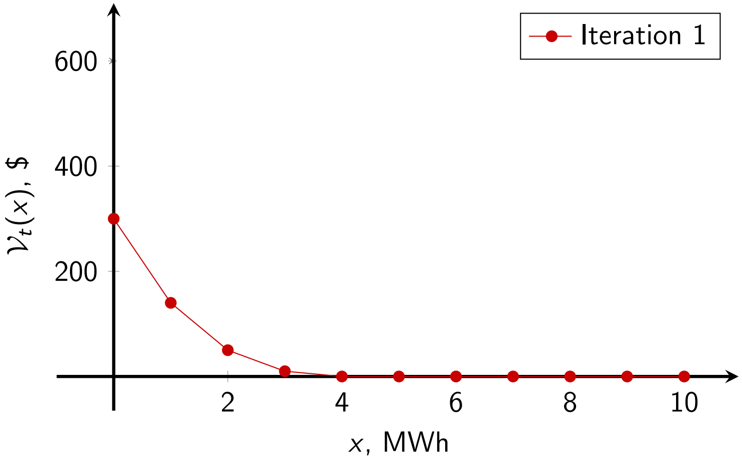

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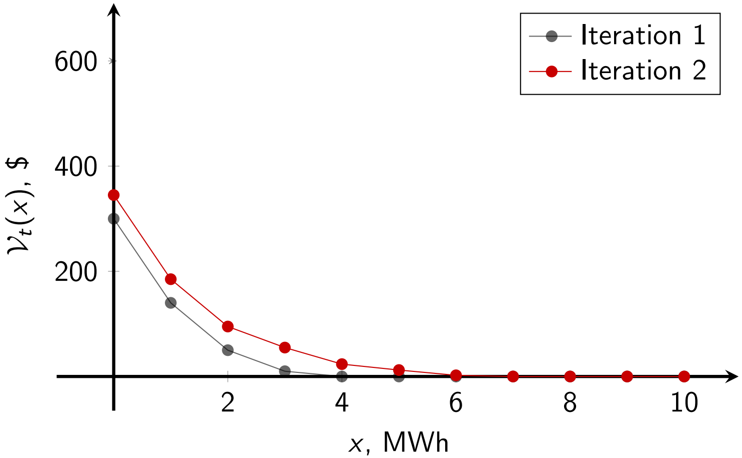

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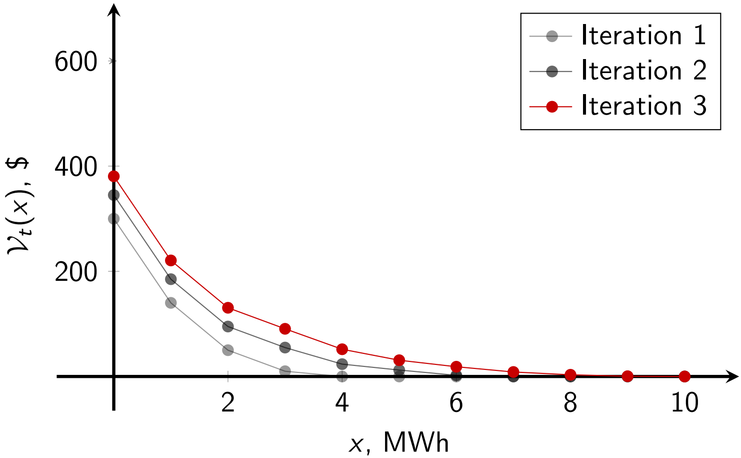

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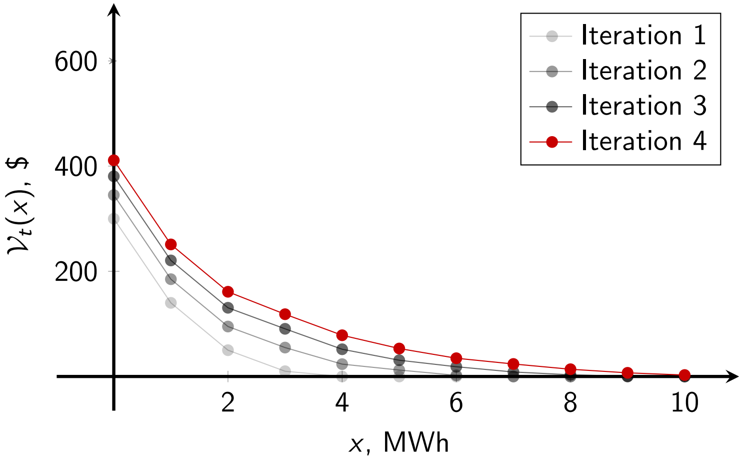

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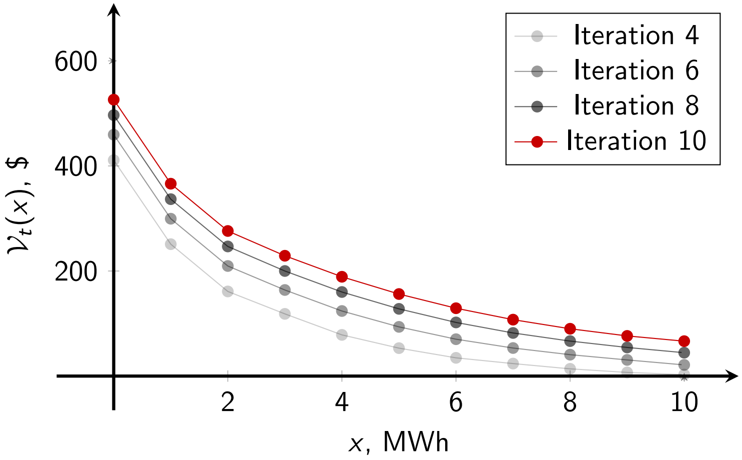

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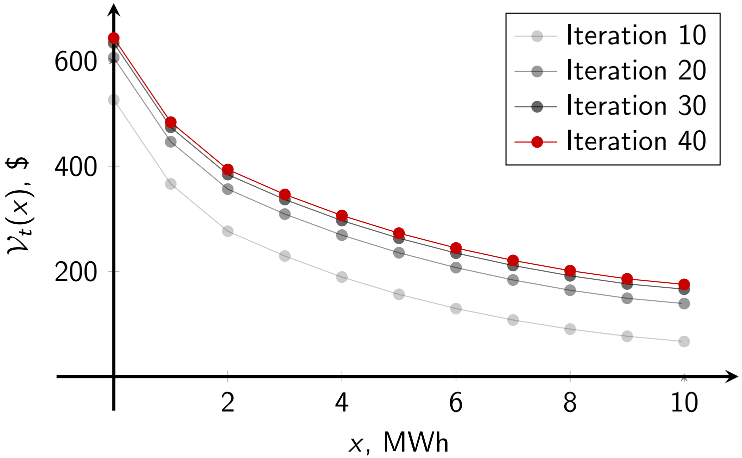

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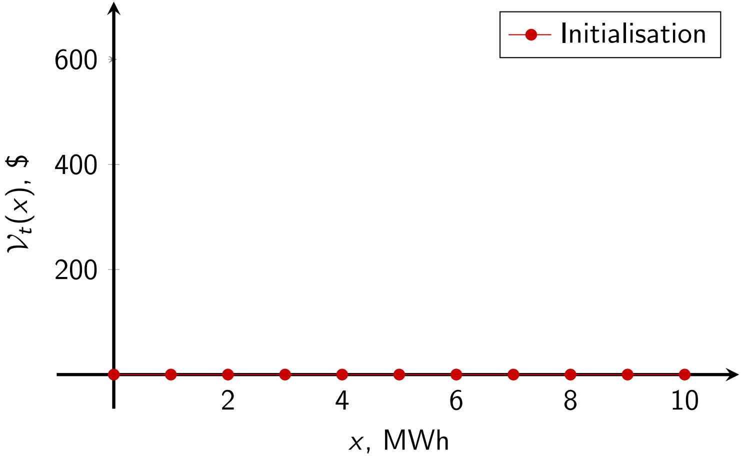

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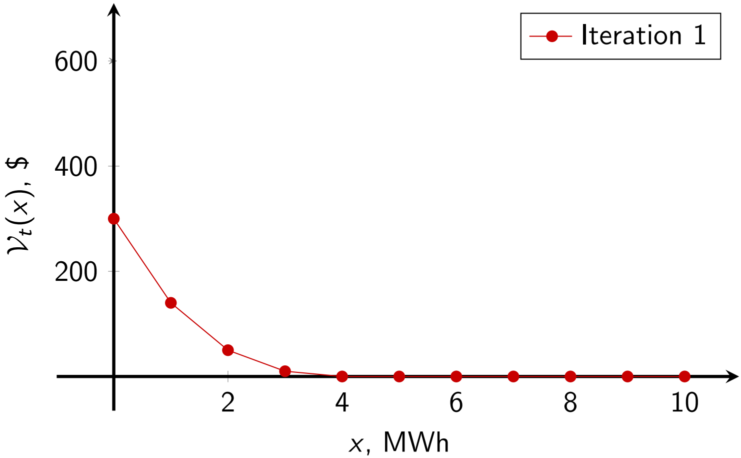

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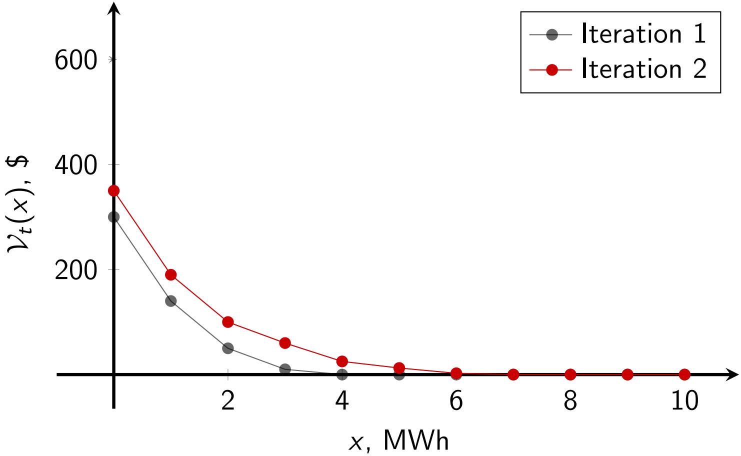

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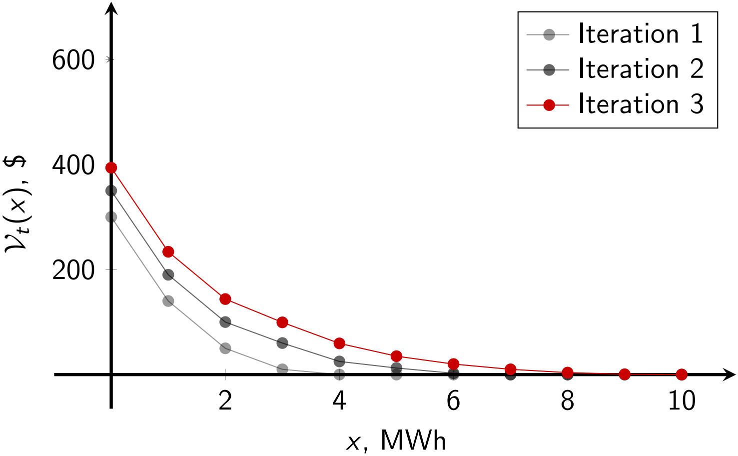

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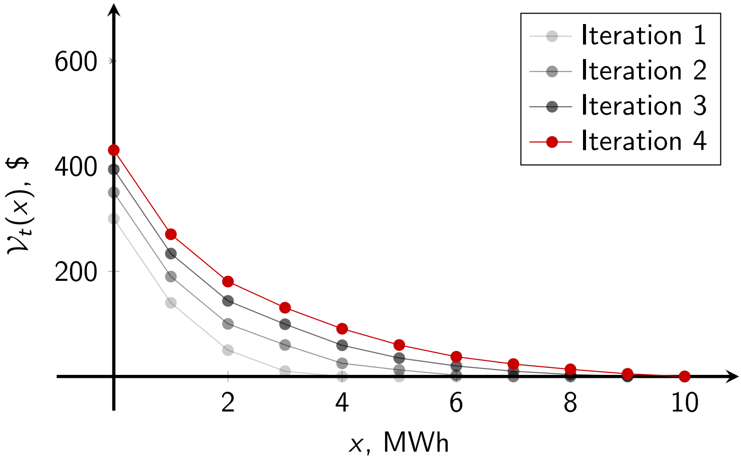

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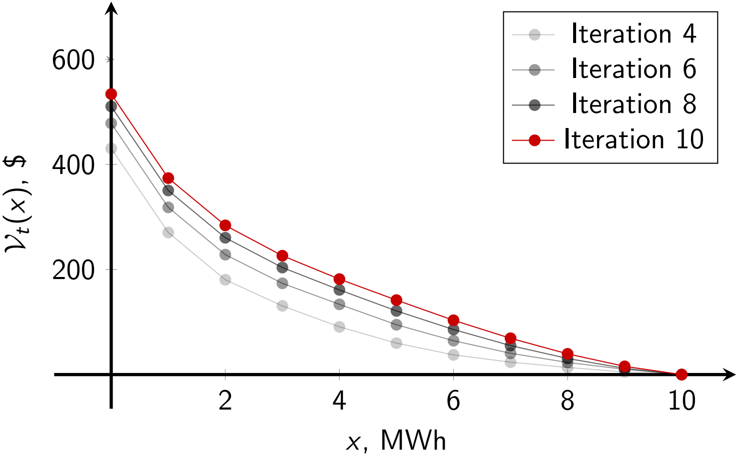

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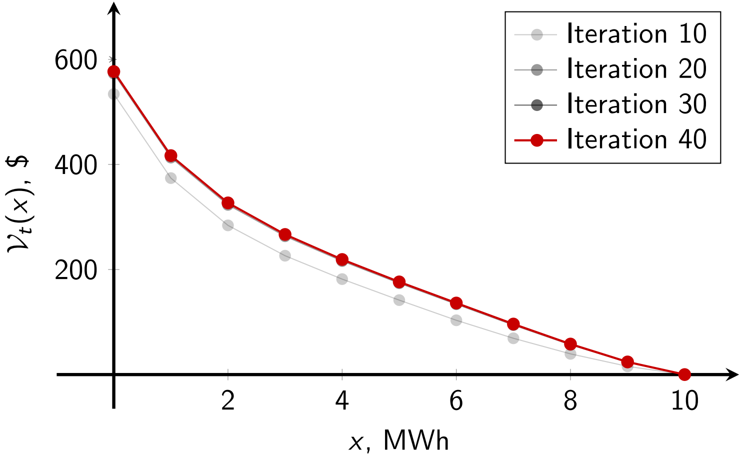

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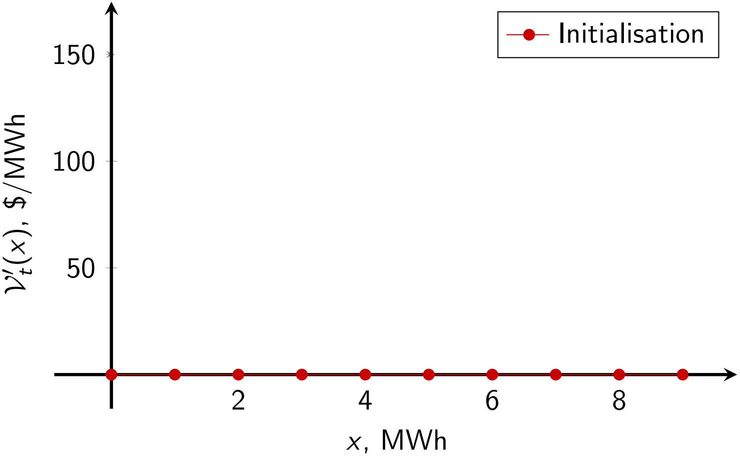

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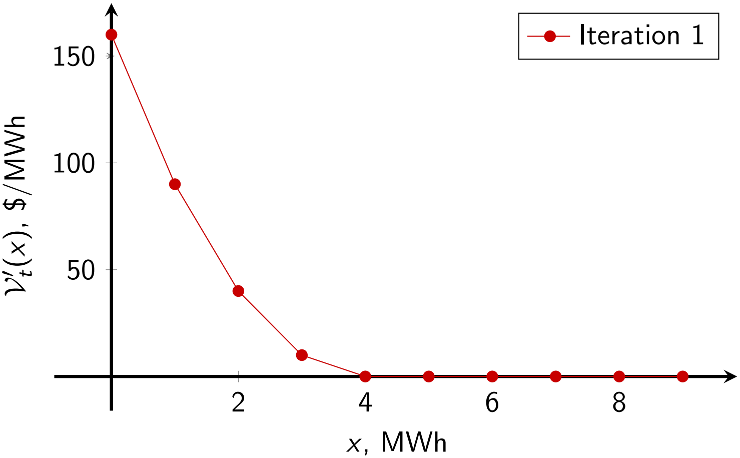

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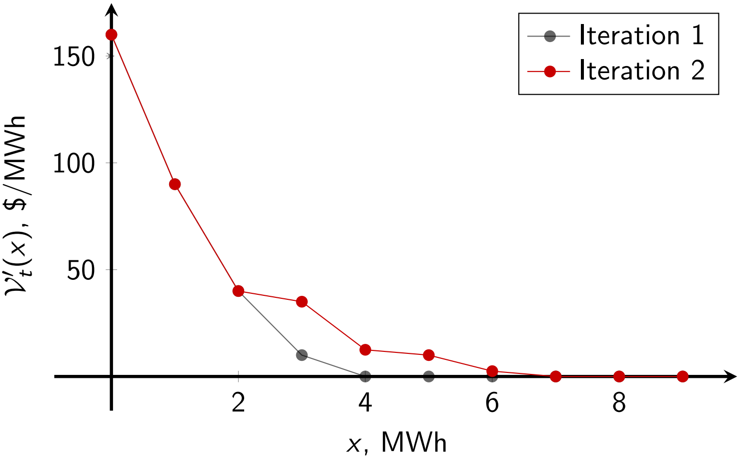

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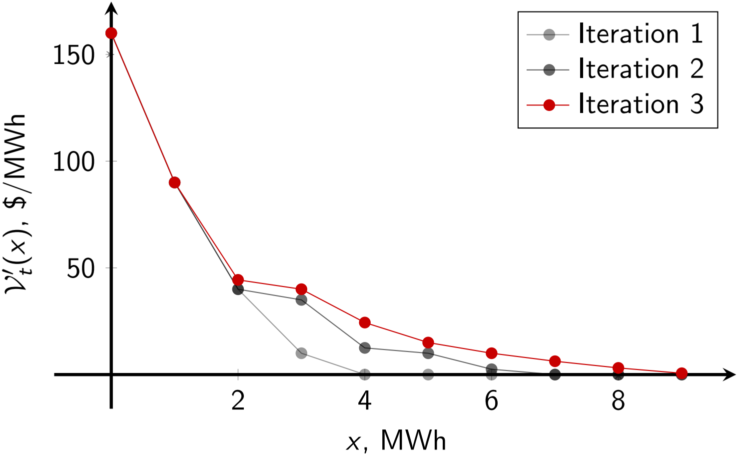

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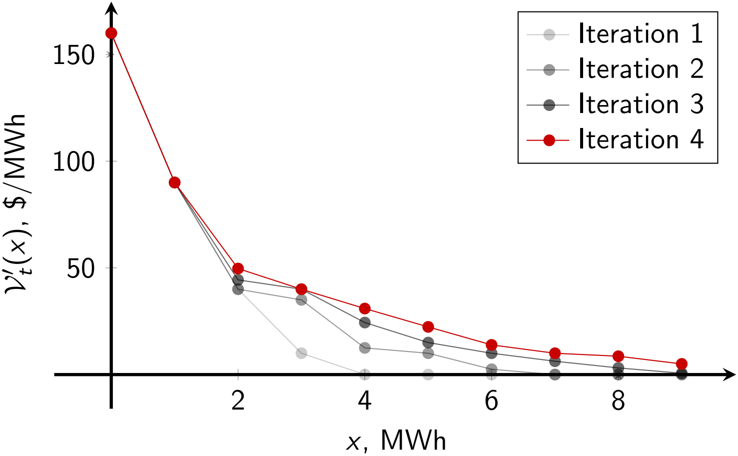

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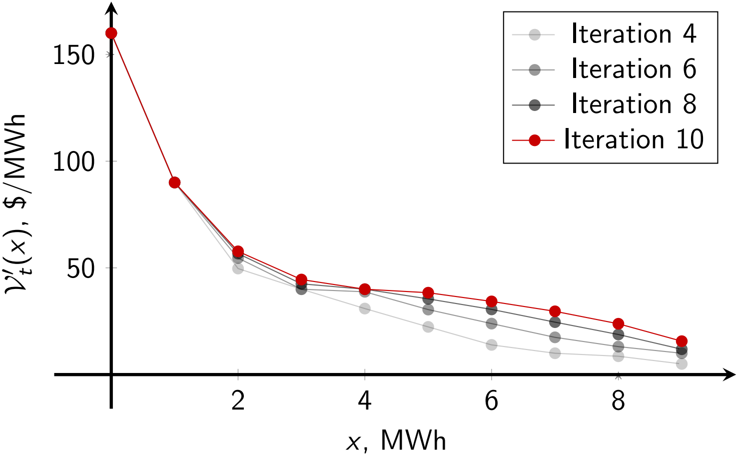

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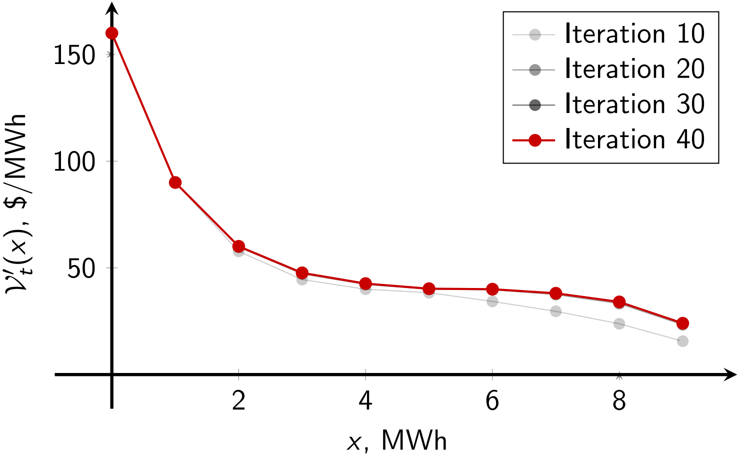

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Infinite Horizon Model

Exogenous Terminal Marginal Water Value

This is the predefined function for $\mathcal{V}_{T+1}(x_{t+1})$ in DOASA

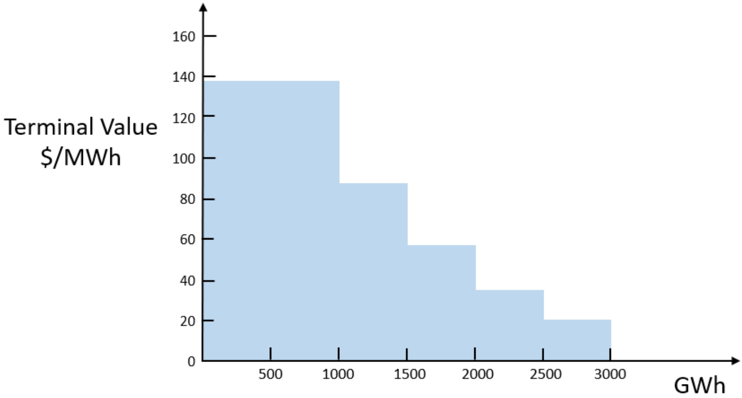

Figure: Marginal value of water in DOASA

Infinite Horizon Model

Endogenous Terminal Marginal Water Value

The difference between the standard SDDP and the infinite horizon SDDP is the transition from an exogenous terminal value of water to an endogenous terminal water of water.

$\mathcal{V}_{T+1}(x_{t+1})$ becomes an approximation like all other stages in SDDP and is refined over the course of the algorithm.

Infinite Horizon Model

Endogenous Terminal Marginal Water Value

Infinite horizon SDDP benefits

1. Flexible to modelling different configurations of NZEM
2. One less assumption in model

Infinite Horizon Model

Standard SDDP Forward Passes

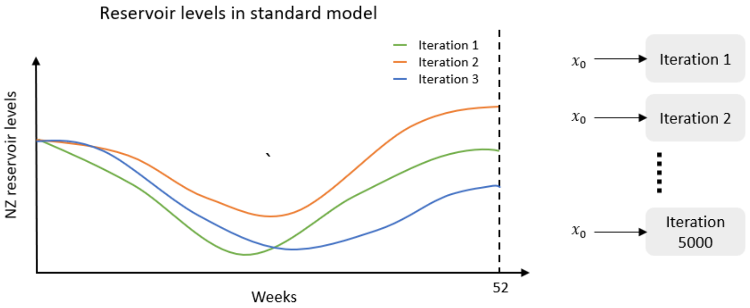

Figure: States in standard SDDP

Infinite Horizon Model

Infinite Horizon SDDP Forward Passes

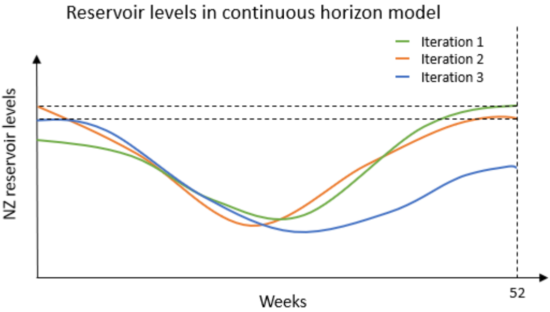

Figure: States in infinite horizon SDDP

Graphic of standard SDDP algorithm applied to NZ Hydro-thermal Scheduling Problem

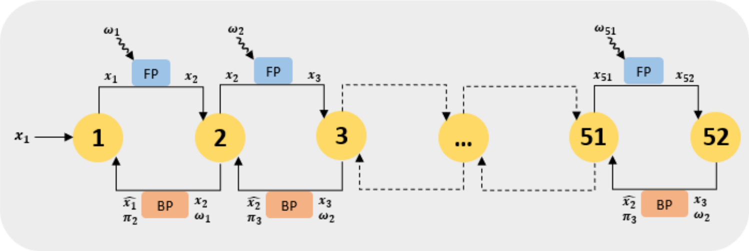

Figure: Standard SDDP model

Infinite Horizon Model

Infinite Horizon SDDP Algorithm

Graphic of infinite horizon SDDP algorithm applied to NZ Hydro-thermal Scheduling Problem

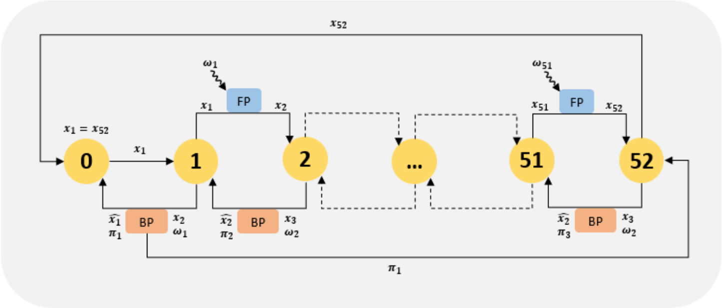

Figure: Infinite Horizon SDDP model

Infinite Horizon Model

Infinite Horizon SDDP Algorithm

The previous slide implied in every of iteration SDDP the terminal cost approximation $\mathcal{V}_{T+1}(x_{t+1})$ is improved.

We found it more efficient to cache the stage 1 cuts for several hundred iterations of SDDP then pass them to stage T.

Infinite Horizon Model

Infinite Horizon SDDP Algorithm

We used an average cost model in our infinite horizon SDDP.

$$\mathcal{V}_{T+1}(x) = \mathcal{V}_1(x) - \Delta, \quad \forall x$$

This means these new cuts from any stage t will be Δ units higher than the previous cuts from stage t.

Δ is expected cost accrued from stages 1 to T.

As these new cuts are Δ units higher than the current cuts, current cuts will be made redundant.

The current cuts provide useful and accurate information about $\mathcal{V}_{T+1}(\cdot)$.

How can we add new cuts without making old cuts redundant?

Our solution

Shift new cuts down by δ^*, a lower bound approximation of Δ (as we do not know the true value of Δ)

δ^i for each cut i is determined by finding the maximum distance distance between the new and current cut surface across set of sampled states.

The set of sampled states is the states (reservoir levels) that cut were previously generated at.

$\delta^* = \min\{\delta_i\}$

The new cuts are shifted vertically down by δ^*

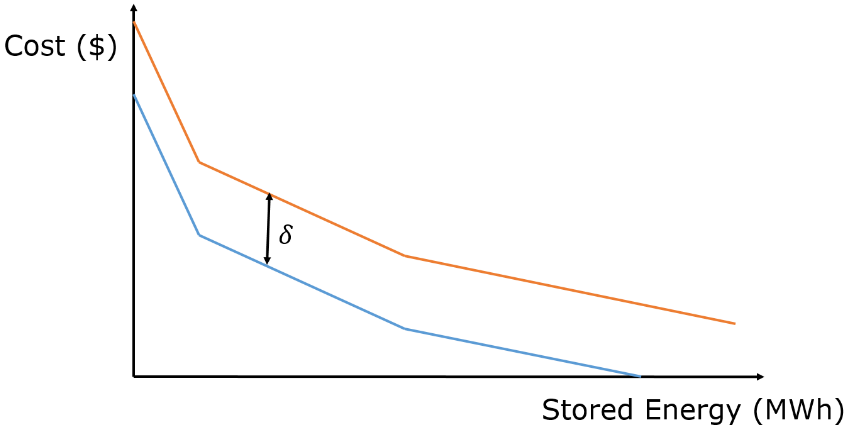

Figure: Plot of new cuts and current cuts 1D dominating approximation

SDDP infinite horizon algorithm overview:

1. Set $i = 0$ and initialise $\mathcal{V}^i_{T+1}(\cdot) = 0$.
2. Run 500 iterations of SDDP.
3. Set $\delta^* = \min_x\{\mathcal{V}^i_1(x) - \mathcal{V}^i_{T+1}(x)\}$.
4. Pass the 500 stage 1 cuts to stage T shifted down by δ^*.
5. If not *converged*: $i = i + 1$, and go to step 2, otherwise end.

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Infinite Horizon Model

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Infinite Horizon Model

Convergence

Convergence of infinite horizon SDDP algorithm will result in a convergence of δ to Δ. This represents a convergence of the hydro-thermal scheduling decision policy.

With a converged Δ the approximation of the terminal cost-to-go functions between "big iterations" are related by

$$\mathcal{V}_1(x) - \mathcal{V}_{T+1}(x) = \Delta, \quad \forall x.$$

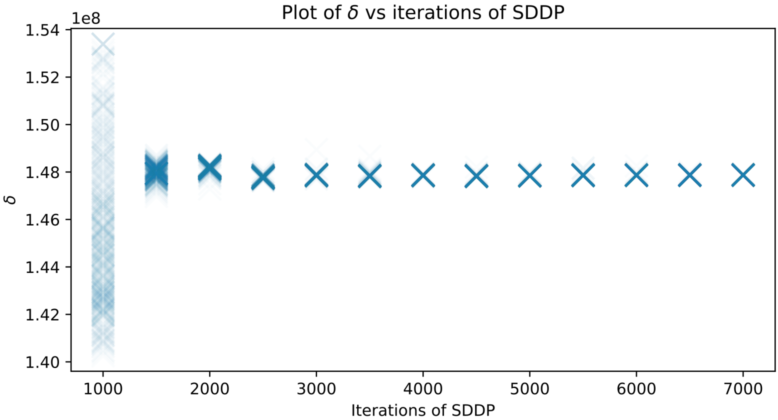
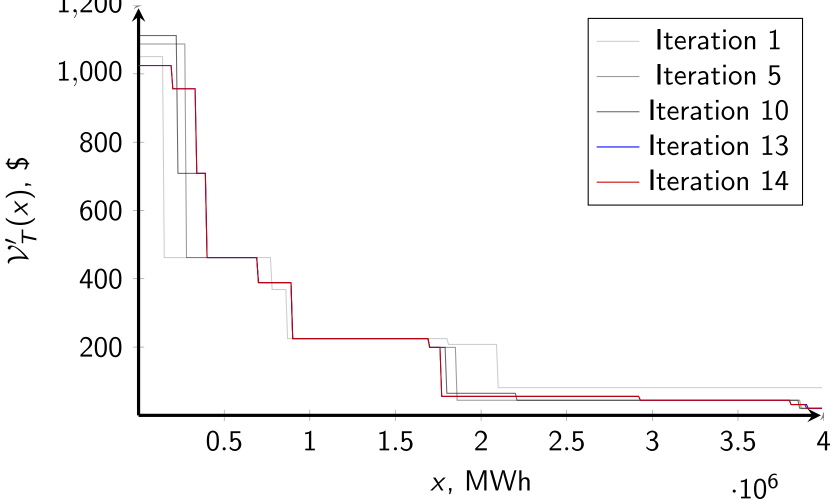


Figure: Plot of δ^i as sampled every 500 iterations

Scenarios

Endogenous Terminal Water Value



Outline

- Model trained using existing hydro and thermal stations, with a different number of units at Huntly Power Station available.
- Demand taken from a single year for consistency.
- Simulated using historical inflow data, 1994–2013.
- Implemented in `JADE`, using `SDDP.jl`.

Scenarios

Running the Model in JADE

- Model trained using existing hydro and thermal stations, with a different number of units at Huntly Power Station available.
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[3] Just Another DOASA Environment.
[4] Dowson and Kapelevich (2017).

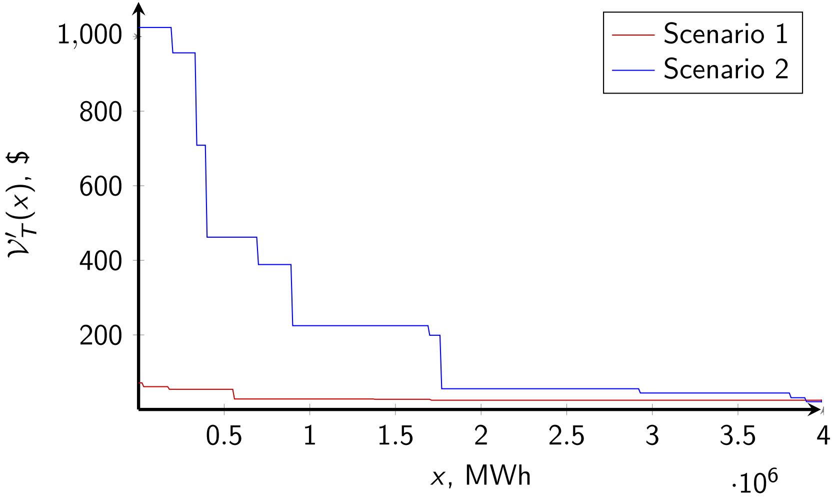
Scenarios

Five Simulations

1. Four Huntly Units (2 Rankines, 2 Gas)
2. Two Huntly Units (2 Gas)
3. No Huntly Units
4. No Thermal Generation
5. Additional Geothermal Energy

Scenarios

Endogenous Terminal Water Value



Scenarios

Scenario 1 - Four Units

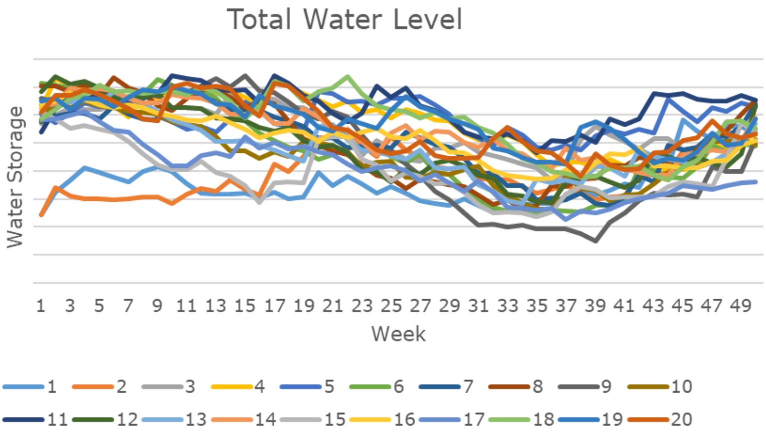


Figure: Plot of Water Level for 20 Years

Scenarios

Scenario 2 - Two Units

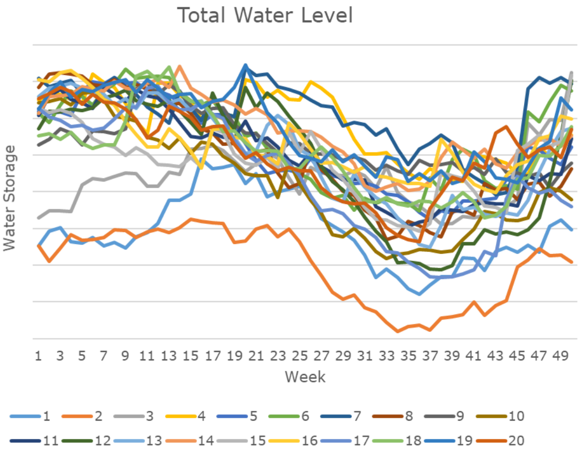


Figure: Plot of Water Level for 20 Years

Scenarios

Scenario 3 - No Huntly

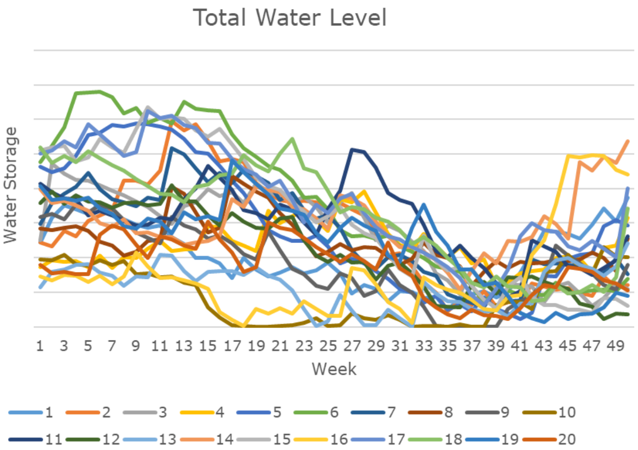


Figure: Plot of Water Level for 20 Years

Scenarios

Scenario 4 - No Thermal

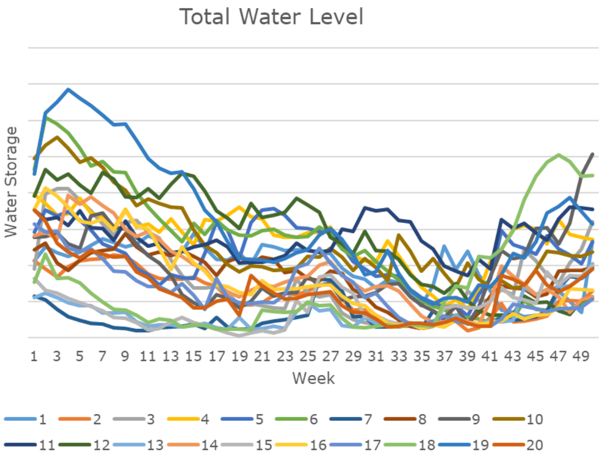


Figure: Plot of Water Level for 20 Years

Scenarios

Scenario 5 - Extra Geothermal Energy

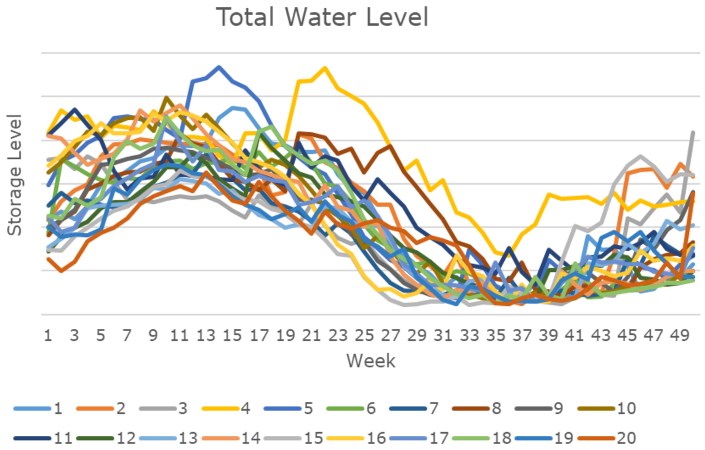


Figure: Plot of Water Level for 20 Years

Scenarios

Comparing Water Levels in 2008

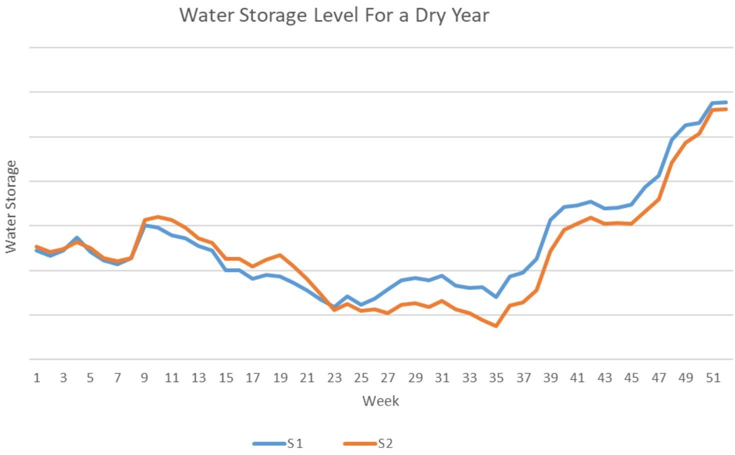


Figure: Total Water Storage with Four and Two Units at Huntly Available

Scenarios

Scenario 1 - Four Units

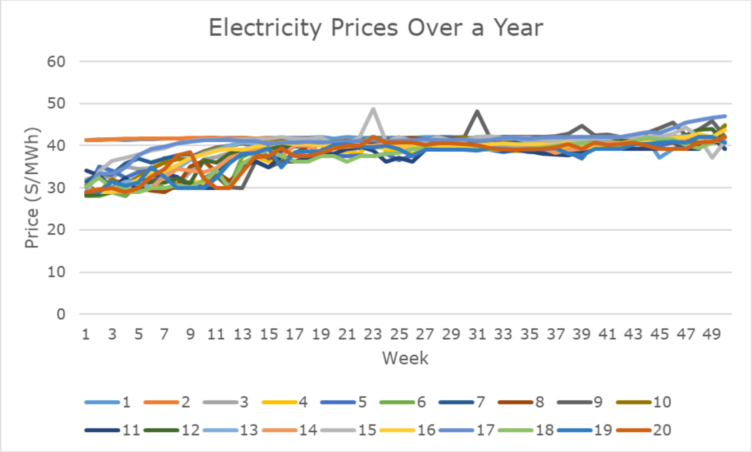


Figure: Plot of Electricity Price - NI Peak

Scenarios

Scenario 2 - Two Units

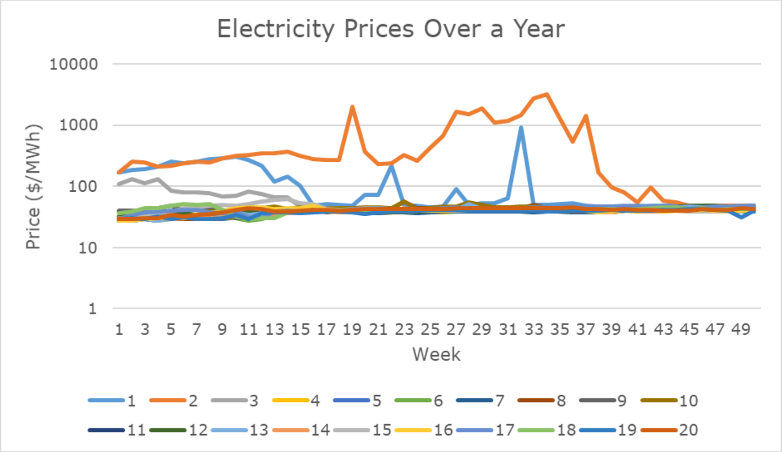


Figure: Plot of Electricity Price - NI Peak

Scenarios

Simulated Financial Outcomes for Gentailers

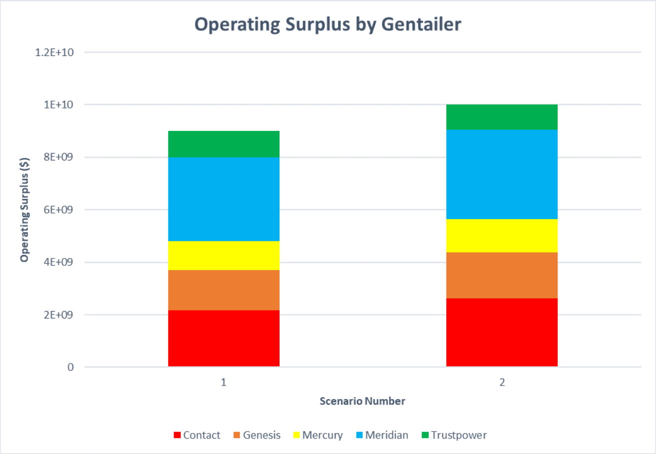


Figure: Operating Surpluses with Four and Two Units at Huntly Available

Scenarios

Greenhouse Gas Emissions

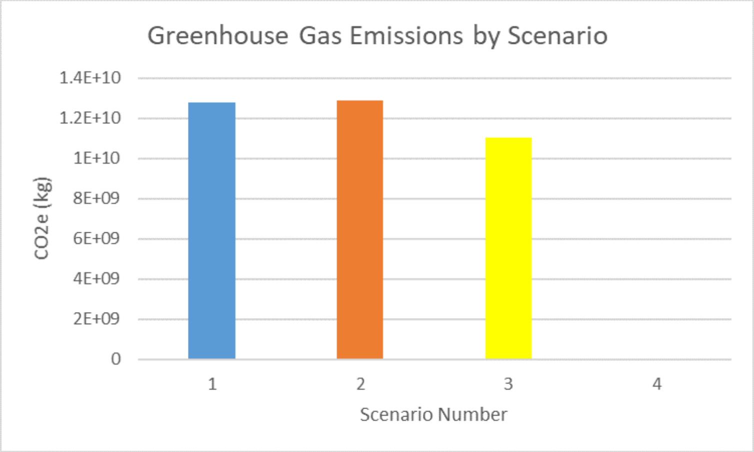


Figure: Emissions with Four and Two Units at Huntly Available

Outline

Remarks

Conclusions

- We have extended the JADE (DOASA) model to incorporate endogenous terminal marginal water values an efficient manner (2-4 hours).
- We have simulated multiple scenarios of thermal availability and explored how the market prices, storage levels, and emissions adapt to these changes.
- We are continuing to refine these scenarios and will investigate the results in wet and dry years, under proposed scenarios for 2035.

Thanks for your attention.

Any questions?

Contact Tony Downward: `a.downward@auckland.ac.nz`