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

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EPOC Winter Workshop, Auckland
September 7, 2018
Outline

Motivation

Background

Multistage stochastic hydro-thermal scheduling

Discrete example

Infinite Horizon Model

Algorithm

Convergence

Scenarios

Remarks

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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.

Over the same period Contact Energy’s Otahuhu B plant (380MW) and Mercury’s Southdown plant (175MW) have both shut down.

Depending on when the last two units shut down there can be serious risks to New Zealand’s electricity supply during dry years.
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Huntly Coal Shutdown

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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.

\(^2\)In a ‘normal’ hydrological year.
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New Zealand’s 100% renewable target

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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.
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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- 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.
In stage $t$, we solve:

$$V_t(x_t, \omega) = \min_{g_t, h_t, x_{t+1}} c_t^\top g_t + \mathbb{E}_{\omega' \in \Omega_{t+1}}[V_{t+1}(x_{t+1}, \omega')],$$

s.t. $x_{t+1} + h_t = x_t + \omega$ [reservoir balance]

$e^\top g_t + e^\top h_t = d_t$ [demand balance]

$g_t, h_t, x_{t+1} \geq 0,$

where $x_t$ is the incoming reservoir levels for stage $t$, $x_t$ is the outgoing reservoir levels, and $\omega$ 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 solve:

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V_t(x_t, \omega) = \min_{g_t, h_t, x_{t+1}} \quad c_t^T g_t + \mathbb{E}_{\omega' \in \Omega_{t+1}}[V_{t+1}(x_{t+1}, \omega')]
\]

s.t. \[
\begin{align*}
  x_{t+1} + h_t &= x_t + \omega \quad \text{[reservoir balance]} \\
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Hydro-thermal scheduling stage-problem

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In stage $T$, we have some predefined function for $V_{T+1}(x_{T+1})$; however, in all other stages, an approximation of $V_t(x_{t+1})$ will be refined over the course of the algorithm.
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For stage $T$, we can set:

$$V_{T+1}(x_{t+1}) = \rho V_1(x_{t+1})$$ [discounted cost model]

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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, $\omega$ MWh, in each stage are uncertain, and occur (and are observed) at the beginning of each stage.
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Discrete Example
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The dynamic programming recursion can be written as follows:

\[ V_t(x) = E_{\omega \in \Omega} \left[ \min_{h \in H} \left\{ C_t(d_t - h) + V_{t+1}(x - h + \omega) \right\} \right]. \]

There are a discrete set of actions \( h \in H \), which must comply with various practical limits:

\[ H \subset \{ h : 0 \leq h \leq \min\{ H, x + \omega \} \}. \]
The dynamic programming recursion can be written as follows:

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

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

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In this simple setting, we will consider the discounted and average cost methods to see how they compare.
The dynamic programming recursion can be written as follows:

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

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In this simple setting, we will consider the discounted and average cost methods to see how they compare.
Discrete Example
Discounted Expected Cost Results

\[ \nu_t(x), \ \$ \]

\[ x, \text{ MWh} \]

- Initialisation
Discrete Example
Discounted Expected Cost Results

\[
V_t(x), \ \$\n\]

\[
x, \ \text{MWh}\n\]
Discrete Example
Discounted Expected Cost Results

\[ V_t(x), \] $\quad x, \text{ MWh} \]
Discrete Example
Discounted Expected Cost Results

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- Iteration 1
- Iteration 2
- Iteration 3
Discrete Example
Discounted Expected Cost Results

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Discounted Expected Cost Results

\[ \nu_t(x), \ $ \]

\[ x, \text{ MWh} \]

- Iteration 4
- Iteration 6
- Iteration 8
- Iteration 10

Graph showing the discounted expected cost results for different iterations.
Discrete Example
Discounted Expected Cost Results

![Graph showing discounted expected cost results for different iterations with points marked for iterations 10, 20, 30, and 40.](image)
Discrete Example
Average Expected Cost Results

\[ \gamma_t(x), \text{ MWh} \]

\[ \mathcal{V}_t(x), \$ \]

Initialisation
Discrete Example
Average Expected Cost Results

\[ y^*_t(x), \$ \]

\[ x, \text{ MWh} \]

Iteration 1
Discrete Example

Average Expected Cost Results

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Discrete Example

Average Expected Cost Results

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\[ x, \text{ MWh} \]

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- Iteration 6
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Discrete Example

Average Expected Cost Results

\[ \nu_t(x), \ $ \]

\[ x, \ \text{MWh} \]

- Iteration 10
- Iteration 20
- Iteration 30
- Iteration 40
Discrete Example
Marginal Cost Results

$y_t'(x), \$/\text{MWh}$

$x, \text{MWh}$

Initialisation
Discrete Example
Marginal Cost Results

\[ \mathcal{V}_t(x), \$/\text{MWh} \]

Iteration 1

\[ x, \text{MWh} \]
Discrete Example
Marginal Cost Results

\[ \nabla'_t(x), \$/\text{MWh} \]

Iteration 1
Iteration 2

\[ x, \text{MWh} \]
Discrete Example
Marginal Cost Results

\[ \nabla_t'(x), \$/\text{MWh} \]

$x, \text{MWh}$

Iteration 1
Iteration 2
Iteration 3
Discrete Example
Marginal Cost Results

\[ \nu_t(x), \$/\text{MWh} \]

Iteration 1
Iteration 2
Iteration 3
Iteration 4

\[ x, \text{MWh} \]
Discrete Example
Marginal Cost Results

\[ \mathcal{V}_t(x), \$/\text{MWh} \]

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- Iteration 6
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\( x, \text{MWh} \)
Discrete Example
Marginal Cost Results

\[ \psi'_t(x), \$/\text{MWh} \]

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\( x, \text{MWh} \)
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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
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. 
$\nu_{T+1}(x_{t+1})$ becomes an approximation like all other stages in SDDP and is refined over the course of the algorithm.
Infinite horizon 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

Reservoir levels in continuous horizon model

Figure: States in infinite horizon SDDP
Infinite Horizon Model

Standard SDDP Algorithm

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

\[ V_{T+1}(x) = V_1(x) - \Delta, \quad \forall x \]

This means these new cuts from any stage \( t \) will be \( \Delta \) units higher than the previous cuts from stage \( t \).

\( \Delta \) is expected cost accrued from stages 1 to \( T \).

As these new cuts are \( \Delta \) units higher than the current cuts, current cuts will be made redundant.

The current cuts provide useful and accurate information about \( V_{T+1}(\cdot) \).

How can we add new cuts without making old cuts redundant?
Our solution
Shift new cuts down by $\delta^*$, a lower bound approximation of $\Delta$ (as we do not know the true value of $\Delta$)

$\delta^i$ 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 $\delta^*$
Figure: Plot of new cuts and current cuts 1D dominating approximation
SDDP infinite horizon algorithm overview:

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

1. Set $i = 0$ and initialise $V_{T+1}^i(\cdot) = 0$.
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Infinite Horizon Model
Infinite Horizon SDDP Algorithm

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2. Run 500 iterations of SDDP.
3. Set $\delta^* = \min_x \{V_1^i(x) - V_{T+1}^i(x)\}$.
4. Pass the 500 stage 1 cuts to stage $T$ shifted down by $\delta^*$.
5. If not converged: $i = i + 1$, and go to step 2, otherwise end.
Convergence of infinite horizon SDDP algorithm will result in a convergence of $\delta$ to $\Delta$. This represents a convergence of the hydro-thermal scheduling decision policy.

With a converged $\Delta$ the approximation of the terminal cost-to-go functions between “big iterations” are related by

$$V_1(x) - V_{T+1}(x) = \Delta, \quad \forall x.$$
Figure: Plot of $\delta^i$ as sampled every 500 iterations
Scenarios

Endogenous Terminal Water Value

\[ \nu_T(x), \$ \]

- Iteration 1
- Iteration 5
- Iteration 10
- Iteration 13
- Iteration 14

\[ x, \text{ MWh} \]
Outline

Motivation

Background
  Multistage stochastic hydro-thermal scheduling

Discrete example

Infinite Horizon Model
  Algorithm
  Convergence

Scenarios

Remarks

Conclusions
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.
- Demand taken from a single year for consistency.
- Implemented in JADE, using SDDP.jl.
Scenarios

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\textsuperscript{3}Just Another DOASA Environment.
\textsuperscript{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

\[ V'_T(x), \ $ \]

\[ x, \ \text{MWh} \]

- Scenario 1
- Scenario 2
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
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
We have extended the JADE (DOASA) model to incorporate endogenous terminal marginal water values in 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?

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