New Modelling Features in JADE

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with acknowledgements to

Vitor de Matos, Geoff Pritchard, Tony Downward, Oscar Dowson, Tuong Nguyen,

Jarand Hole, and many Engineering Honours students

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Outline

What is JADE?

Inflow modelling for testing policies

FUELJADE: Modelling fuel constraints

Risk modelling and transmission

Capacity expansion modelling

FROST: a snowpack model

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What is JADE?

JADE.jl is a hydrothermal reservoir optimization model of the New Zealand electricity system that minimizes expected discounted social cost. It applies the stochastic dual dynamic programming algorithm as implemented in the Julia package SDDP.jl developed by Oscar Dowson.

JADE.jl is made available by Electricity Authority at

https://www.emi.ea.govt.nz/Wholesale/Tools/JADE

and source is on github at

https://github.com/EPOC-NZ/JADE.jl

What is SDDP.jl ?

- open source Julia implementation of SDDP maintained by Oscar Dowson.
- built on JuMP.jl modelling language.
- supports a number of open-source and commercial solvers.
- support for:
  - infinite horizon problems
  - convex risk measures
  - mixed-integer state and control variables
  - partially observable stochastic processes

https://odow.github.io/SDDP.jl/stable/

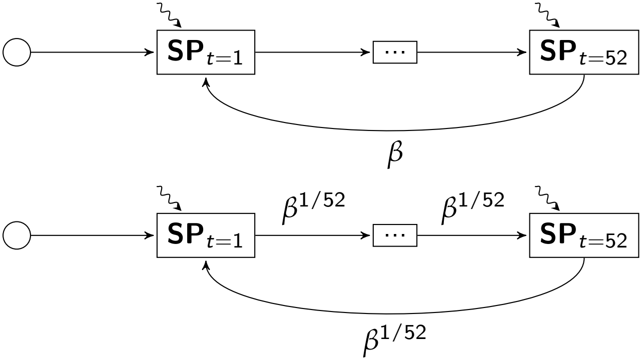
Advantages of JADE

- JADE is used by the Electricity Authority (EA) to monitor the wholesale market and security of supply.
- Wholesale market input data is curated by the EA.
- Open source versus proprietary software.
- No software licence fees (except possibly for LP solver).
- `SDDP.jl` algorithm is based on published research.
- `JuMP` model makes changes easy to implement.
- Policy graph features of `SDDP.jl` make JADE very flexible.

JADE policy graph for a planned year

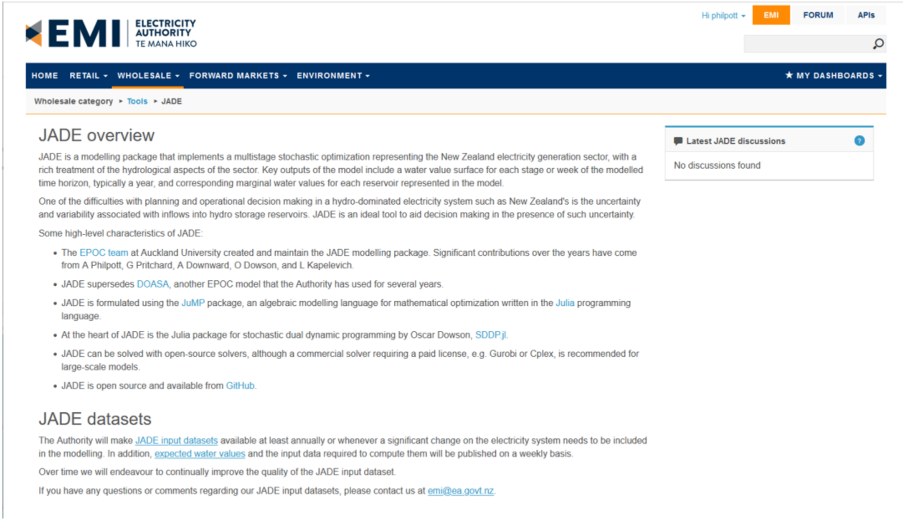
- 52 weekly stages
- $\mathbf{SP}_{t=52}$ has terminal future-cost function

JADE steady-state policy graph



- 52 weekly stages
- annual (weekly) discount factors β ($\beta^{1/52}$) on edges

JADE at the Electricity Authority



EMI | ELECTRICITY AUTHORITY TE MANA HIKO

Hi philpott | EMI | FORUM | APIs

HOME | RETAIL | WHOLESALE | FORWARD MARKETS | ENVIRONMENT | ★ MY DASHBOARDS

Wholesale category ▸ Tools ▸ JADE

JADE overview

JADE is a modelling package that implements a multistage stochastic optimization representing the New Zealand electricity generation sector, with a rich treatment of the hydrological aspects of the sector. Key outputs of the model include a water value surface for each stage or week of the modelled time horizon, typically a year, and corresponding marginal water values for each reservoir represented in the model.

One of the difficulties with planning and operational decision making in a hydro-dominated electricity system such as New Zealand's is the uncertainty and variability associated with inflows into hydro storage reservoirs. JADE is an ideal tool to aid decision making in the presence of such uncertainty.

Some high-level characteristics of JADE:

- The EPOC team at Auckland University created and maintain the JADE modelling package. Significant contributions over the years have come from A Philpott, G Pritchard, A Downward, O Dowson, and L Kapelevich.
- JADE supersedes DOASA, another EPOC model that the Authority has used for several years.
- JADE is formulated using the JuMP package, an algebraic modelling language for mathematical optimization written in the Julia programming language.
- At the heart of JADE is the Julia package for stochastic dual dynamic programming by Oscar Dowson, SDDP.jl.
- JADE can be solved with open-source solvers, although a commercial solver requiring a paid license, e.g. Gurobi or Cplex, is recommended for large-scale models.
- JADE is open source and available from GitHub.

JADE datasets

The Authority will make JADE input datasets available at least annually or whenever a significant change on the electricity system needs to be included in the modelling. In addition, expected water values and the input data required to compute them will be published on a weekly basis.

Over time we will endeavour to continually improve the quality of the JADE input dataset.

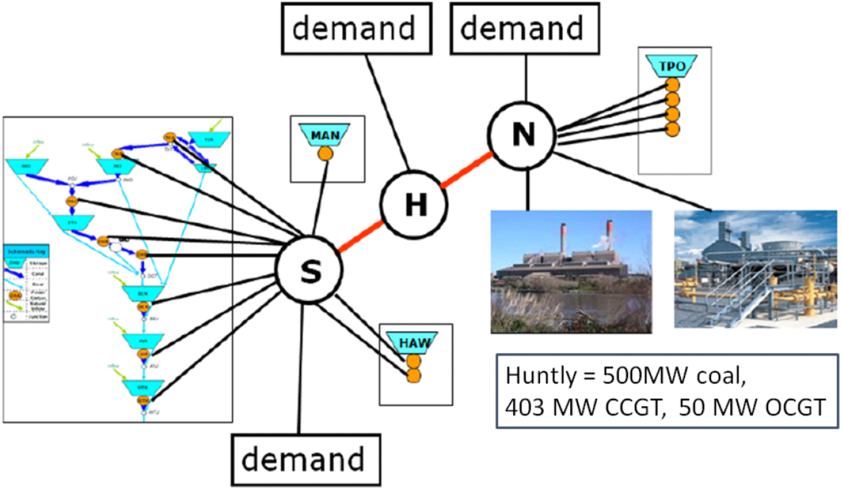
If you have any questions or comments regarding our JADE input datasets, please contact us at emi@ea.govt.nz.

Latest JADE discussions

No discussions found

JADE page at the Electricity Authority: www.emi.ea.govt.nz/Wholesale/Tools/JADE

JADE model implemented at Electricity Authority



SPD network is approximated by a 3-node transmission system. Note: Huntly capacity is out of date and EMI now records 3 Rankines.

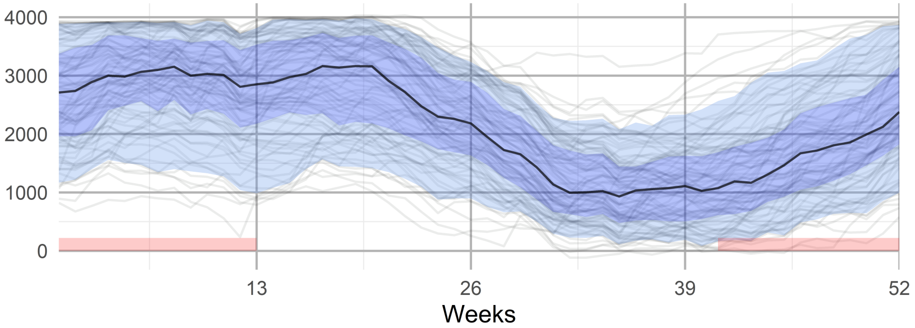
Inputs to JADE

There are 14 core input files that JADE reads in when building the model of the electricity system.

- demand blocks, fixed generation and load shedding costs;
- historical inflows, hydro network arcs + constraints;
- hydro stations (capacity & efficiency), and reservoir limits;
- thermal stations (capacity & heat rate) and fuel costs;
- transmission network (line capacities & losses);
- outages of stations and transmission lines;
- EOH cuts file from steady-state solution.

JADE in steady state

- Infinite horizon EMI JADE computes EOH cuts defining the terminal future cost function at the end of the plan year.
- EOH cuts are added to finite horizon model.
- Any infinite horizon policy can be simulated with 92 consecutive years of inflows (1932-2023)



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Inflow modelling in SDDP

- Inflows are modelled so we can compute a policy using SDDP.
- PSR SDDP takes historical inflows and fits a PAR model.
  - PAR model is linear in inflows and needs adjustments to prevent negative inflows.
  - Some evidence that this gives optimistic policies.
- Academic versions of JADE by EPOC researchers have tried...
  - independent inflows with DIA (doasa);
  - an AR1 model in the logs of inflows (Adam Clifford, 2022);
  - a model with Markov ENSO states (Xander Butler, 2023);

In-sample versus out-of-sample performance

- Convergence of SDDP to an "optimal" policy simulates with the same distribution that we use to construct the policy.
- In its simplest form this works with stagewise independent inflows as in EMI JADE.
- How will it work if we assume historical inflows 1932-2023?
- If this is our KPI, then should we train (overfit?) SDDP on this history?
- How will it work in practice?
- To test we need a set of synthetic inflows that is not history but has the same distribution.

Spatial correlation

	Matahina	Mangahao	Moawhango	Rotoaira	Taupo	Arapuni	Vaikaremoan	Cobb	Coleridge	Tekapo	Pukaki	Ohau	Benmore	Hawea	Wanaka	Dunstan	Manapouri
Matahina	1.000	0.177	0.556	0.708	0.731	0.693	0.401	0.280	0.174	-0.033	-0.113	-0.023	0.059	0.053	-0.019	0.019	-0.043
Mangahao	0.177	1.000	0.275	0.373	0.360	0.235	0.069	0.294	0.257	0.099	0.032	0.140	0.172	0.189	0.089	0.128	0.225
Moawhango	0.556	0.275	1.000	0.855	0.760	0.528	0.239	0.336	0.294	-0.008	-0.129	0.022	0.125	0.136	0.030	0.110	0.044
Rotoaira	0.708	0.373	0.855	1.000	0.965	0.711	0.334	0.446	0.317	0.029	-0.099	0.055	0.156	0.170	0.047	0.121	0.055
Taupo	0.731	0.360	0.760	0.965	1.000	0.722	0.350	0.426	0.298	0.036	-0.079	0.058	0.159	0.156	0.063	0.124	0.045
Arapuni	0.693	0.235	0.528	0.711	0.722	1.000	0.342	0.354	0.199	-0.072	-0.169	-0.042	0.050	0.069	-0.064	0.021	0.009
Waikaremoana	0.401	0.069	0.239	0.334	0.350	0.342	1.000	0.084	0.000	-0.204	-0.247	-0.211	-0.139	-0.141	-0.197	-0.160	-0.199
Cobb	0.280	0.294	0.336	0.446	0.426	0.354	0.084	1.000	0.306	0.227	0.097	0.264	0.330	0.367	0.188	0.229	0.289
Coleridge	0.174	0.257	0.294	0.317	0.298	0.199	0.000	0.306	1.000	0.246	0.099	0.284	0.358	0.334	0.279	0.338	0.258
Tekapo	-0.033	0.099	-0.008	0.029	0.036	-0.072	-0.204	0.227	0.246	1.000	0.886	0.900	0.795	0.751	0.726	0.589	0.464
Pukaki	-0.113	0.032	-0.129	-0.099	-0.079	-0.169	-0.247	0.097	0.099	0.886	1.000	0.850	0.677	0.633	0.651	0.468	0.404
Ohau	-0.023	0.140	0.022	0.055	0.058	-0.042	-0.211	0.264	0.284	0.900	0.850	1.000	0.899	0.877	0.772	0.662	0.618
Benmore	0.059	0.172	0.125	0.156	0.159	0.050	-0.139	0.330	0.358	0.795	0.677	0.899	1.000	0.862	0.802	0.767	0.583
Hawea	0.053	0.189	0.136	0.170	0.156	0.069	-0.141	0.367	0.334	0.751	0.633	0.877	0.862	1.000	0.690	0.634	0.711
Wanaka	-0.019	0.089	0.030	0.047	0.063	-0.064	-0.197	0.188	0.279	0.726	0.651	0.772	0.802	0.690	1.000	0.875	0.464
Dunstan	0.019	0.128	0.110	0.121	0.124	0.021	-0.160	0.229	0.338	0.589	0.468	0.662	0.767	0.634	0.875	1.000	0.459
Manapouri	-0.043	0.225	0.044	0.055	0.045	0.009	-0.199	0.289	0.258	0.464	0.404	0.618	0.583	0.711	0.464	0.459	1.000

Spatial correlation of historical log(inflow) 1932-2025.

Modified Fractional Gaussian Noise

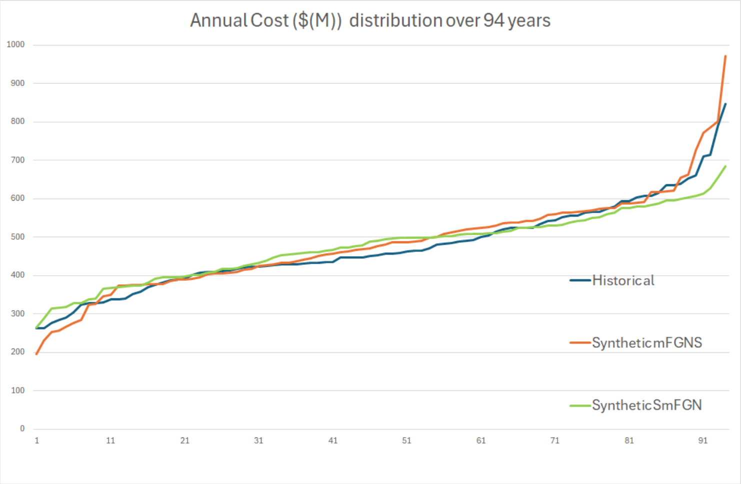
[Kirsch, B. R. et al, 2013, Chadwick, C. et al, 2024]

- Transform logarithms of inflows to have mean 0, variance 1.
- Establish correlations between transformed log inflows in space and time.
- Create synthetic multivariate normal random variables of scaled log inflows with $\mathcal{N}(0,1)$ marginals.
- SmFGN: spatial then temporal; mFGNS:temporal then spatial.
- Either ...
  - Transform marginals to $\mathcal{N}(\mu,\sigma^2)$ and exponentiate, or
  - Recreate marginal inflows from $\mathcal{N}(0,1)$ using NORTA[2].

[2] Cario, M.C. and Nelson, B.L., 1997

Synthetic mFGN/NORTA versus Historical

[Wendy Liou and Shahed Ismael, 2025]



Cost duration curves from JADE policy simulated with 94 synthetic mFGN/NORTA inflows and historical inflows 1932-2025.

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Fuel constraints

- What about gas availability?
- EMI version of JADE.jl assumes exogenous forecast of gas and coal prices for electricity generation.
- These prices will actually be uncertain and endogenous, i.e., depend on how much is still in the ground and what thermal electricity generation has occurred.
- But electricity generation depends on the JADE policy and on the inflows observed.

FUELJADE model

- Fuel is a state variable in FUELJADE.
- Fuel is purchased once in stage 1 and then is consumed over the year from a fuel stockpile at zero variable cost.
- Purchases in stage 1 of FUELJADE will be dependent on fuel state and other states (reservoir levels) but not on anticipated future inflows.
- Policy computes a marginal fuel value as well as a marginal water value. These are opportunity costs of using fuel and water respectively.

The code in model.jl

```
#--------------------------------------------------------------------
# State variable: fuel stocks for each thermal plant in GJ
#--------------------------------------------------------------------
@variable(
    md,
    0.0 <= fuelstock[m in s.THERMALS],
    SDDP.State,
    initial_value = 0.0
)
```

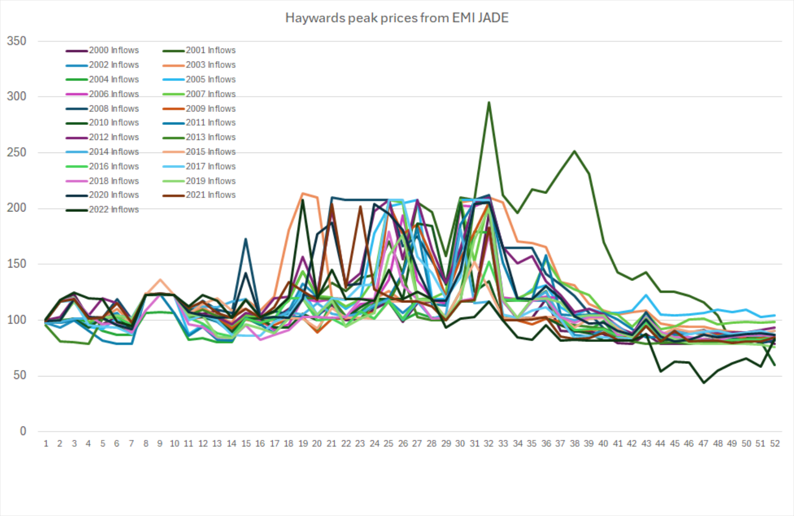
```
@constraints(
    md,
    begin
# Conservation for fuel
fbalance[m in s.THERMALS], (fuelstock[m].out - fuelstock[m].in) == fuel_buy[m] -
sum(d.durations[timenow][bl]*(thermal_use[m, bl])*d.thermal_stations[m].heatrate for bl in
s.BLOCKS)
    end
        )
```

Fuel is a state variable that is replenished only in stage 1 and consumed in all stages.

FUELJADE model experiments

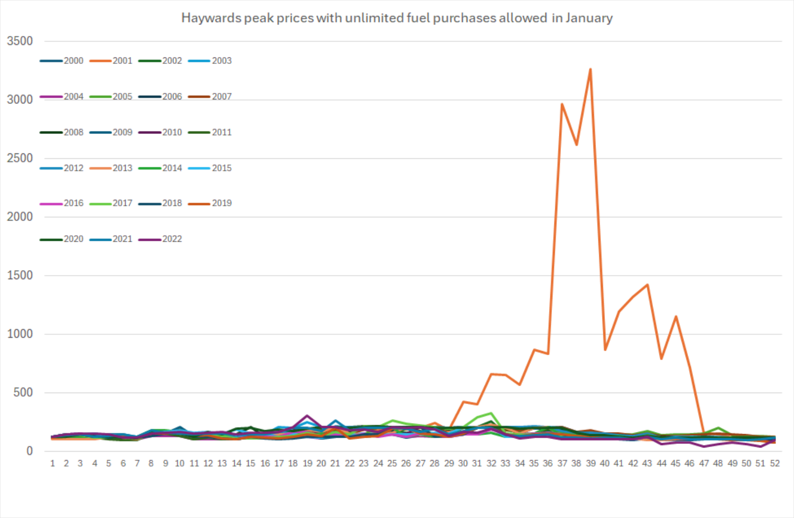
- Compute a JADE policy for 2024 using EMI fuel cost data.
  - Train steady-state problem for 2024 (5000 iterations)
  - Train 2024 finite horizon problem with EOH cuts (5000 iterations)
- Compute a FUELJADE policy for 2024.
  - Train steady-state problem for 2024 with unlimited purchase of fuel in stage 1 at January 2024 fuel prices (5000 iterations).
  - Train 2024 finite horizon problem with EOH cuts and unlimited fuel purchase in stage 1 (5000 iterations).
  - Train 2024 finite horizon problem with EOH cuts but limited fuel purchases in stage 1 (5000 iterations).

Peak forecast prices at Haywards 2024: EMI JADE



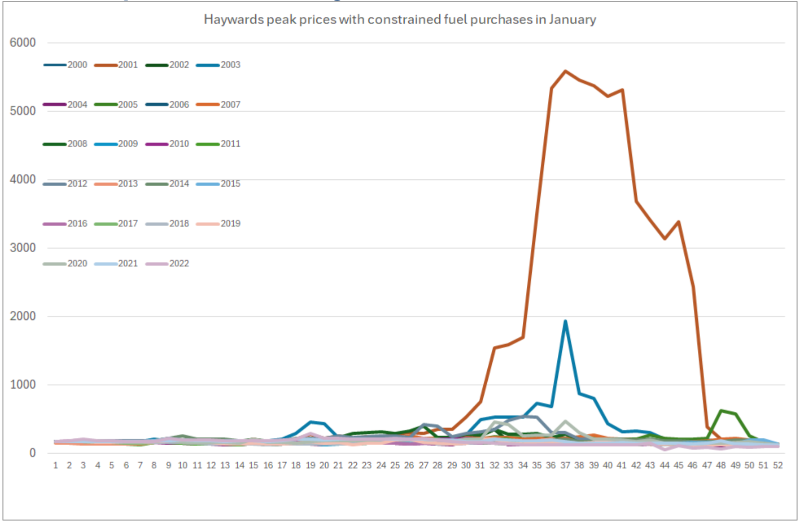
Peak prices ($/MWh) at Haywards in 2024 forecast from EMI JADE for 22 inflow years.

Peak forecast prices at Haywards 2024: FUELJADE



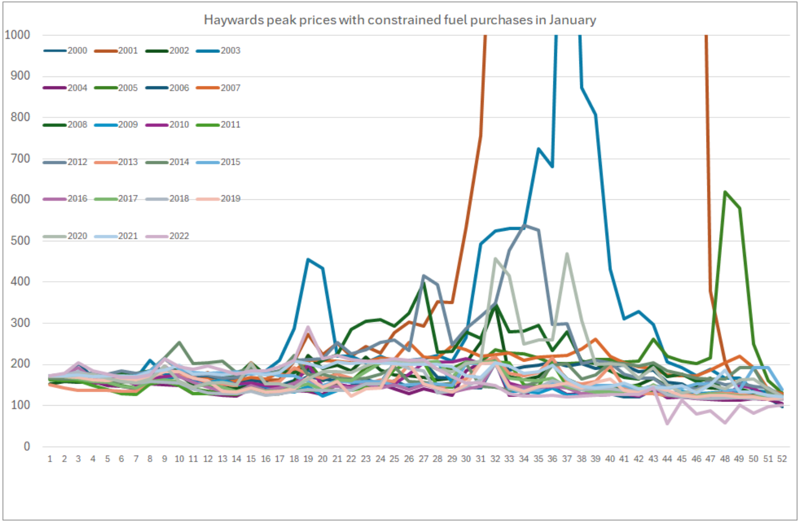
Peak prices ($/MWh) at Haywards in 2024 forecast from FUELJADE for 22 inflow years.
Unlimited fuel purchases allowed in January.

Peak forecast prices at Haywards 2024: FUELJADE



Peak prices ($/MWh) at Haywards in 2024 forecast from FUELJADE for 22 inflow years.
Maximum January fuel purchase = 2024 historical fuel usage.

Peak forecast prices at Haywards 2024: FUELJADE (detail)



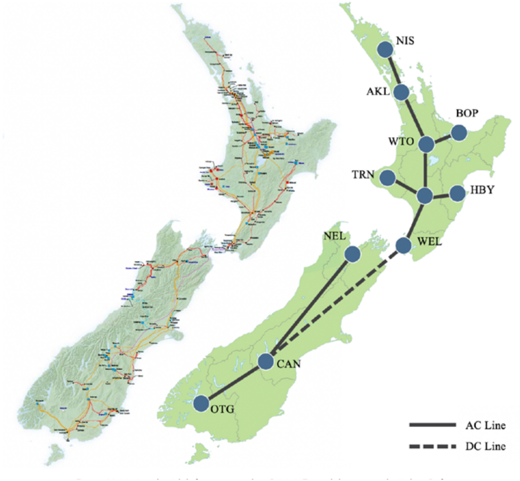
Peak prices ($/MWh) at Haywards in 2024 forecast from FUELJADE for 22 inflow years.
Maximum January fuel purchase = 2024 historical fuel usage.

Outline

Risk and transmission constraints in JADE

- Risk modelling is a current feature of JADE.jl and can be included using commands in JADE run file. But risk aversion is not applied in data sets on EMI.
- JADE.jl allows user to alter transmission grid in data files. EMI version uses a 3-node grid (as above).

EPOCJADE: A more detailed transmission network



In EPOCJADE.jl, SPD network on left is approximated by an 11-node transmission system

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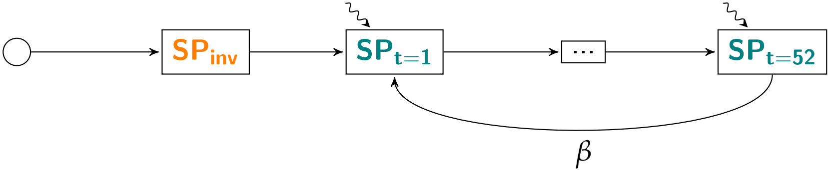
EPOCJADE capacity planning

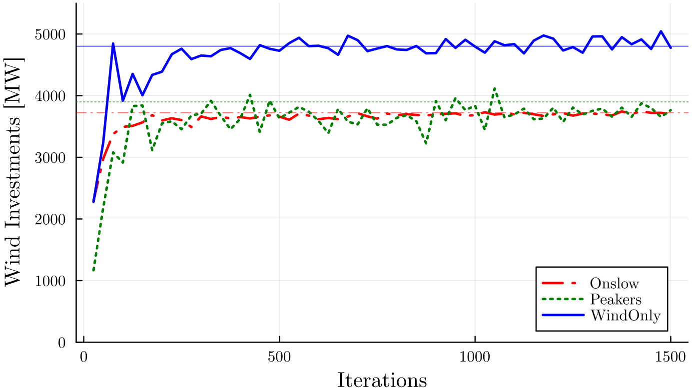
[Hole et al, 2024]



Add capacity investment node $\mathbf{SP_{inv}}$ to the steady-state policy graph.

Investments in new wind capacity with different backup

Three cases: Pump storage, Peakers, None



Investment decisions for new wind capacity in the three different cases against the number of SDDP training iterations. The investment decisions are evaluated every 25 iterations.

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FROST coming soon

Framework for Reservoir Optimization

with

Snowpack and Temperature

The End

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References

- Chadwick, C., Babonneau, F., Homem-de-Mello, T., & Letelier, A., 2024. Synthetic simulation of spatially-correlated streamflows: Weighted-modified Fractional Gaussian Noise. Water Resources Research, 60.
- Cario, M.C. and Nelson, B.L., 1997. Modeling and generating random vectors with arbitrary marginal distributions and correlation matrix (pp. 1-19). Technical Report, Department of Industrial Engineering and Management Sciences, Northwestern University, Evanston, Illinois.
- Ghosh, S. and Henderson, S.G., 2003. Behavior of the NORTA method for correlated random vector generation as the dimension increases. ACM Transactions on Modeling and Computer Simulation (TOMACS), 13(3), pp.276-294.
- Hole, J., Philpott, A.B. and Dowson, O., 2025. Capacity planning of renewable energy systems using stochastic dual dynamic programming. European Journal of Operational Research, 322(2), pp.573-588.

References

- Kirsch, B. R., Characklis, G. W., & Zeff, H. B., 2013. Evaluating the impact of alternative hydro-climate scenarios on transfer agreements: Practical improvement for generating synthetic streamflows. Journal of Water Resources Planning and Management, 139(4), 396–406.