EMERALD: a green GEM

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Joint work with Anthony Downward and Regan Baucke

Electric Power Optimization Centre
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www.epoc.org.nz

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What is EMERALD?

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- JuDGE visualizations enable one to explore the optimal expansion plan.
- This talk presents a summary and some results of EMERALD.

Outline

Multi-horizon modelling and JuDGE

- Multi-horizon stochastic programming and capacity planning
- The JuDGE package

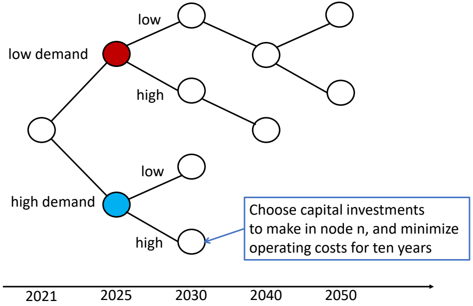
EMERALD demonstration

- The New Zealand model
- Demonstration
- Results

Central planning versus commercial investment

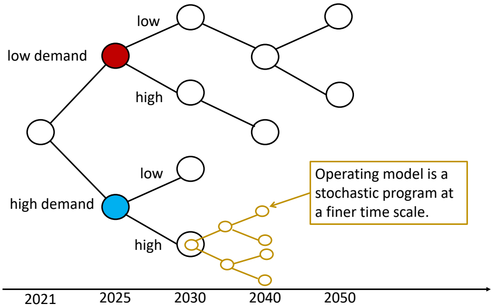
Outline

Multi-horizon planning

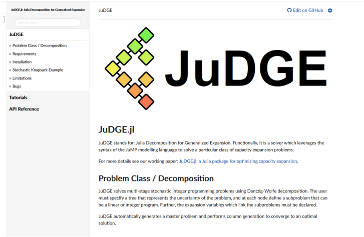


Capacity-expansion decisions over longer time scale (5 years or 10 years) result in lower operational costs, or higher revenue in the future.

Multi-horizon scenario trees



Operational decisions with short-term uncertainty optimized by a stochastic program.



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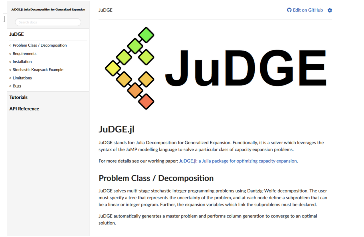
JuDGE stands for Julia Decomposition for Generalized Expansion.).

- allows users to easily implement multi-horizon optimization models using the JuMP modelling language;
- can apply end-of-horizon risk-measures in objective function and/or the constraints; and
- outputs an interactive view of the results over the scenario tree, enabling decision makers to explore the optimal expansion plan.



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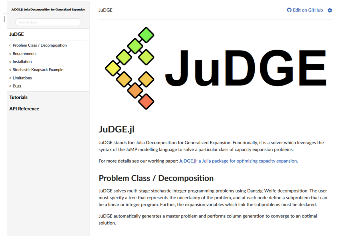

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JuDGE modelling framework

To apply JuDGE we require...

- a tree with corresponding data and probabilities for each node;
- a subproblem defined as a JuMP model for each node in the tree; and
- expansion (and/or shutdown) decisions and costs;
- a choice of solver for master and subproblem.

JuDGE automatically forms a restricted master problem, and applies Dantzig-Wolfe decomposition.[2]

The LP relaxation of the restricted master problem is typically solved with an interior point method, and the subproblems are solved as mixed-integer programs.

JuDGE can formulate the deterministic equivalent problem directly as a JuMP model (mixed-integer program).

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Outline

The New Zealand model

Expansions and shutdowns

Optimize capacity expansion in response to uncertainty represented by a scenario tree.

Model is a risk-averse central-planning model minimizing discounted disbenefit Z summed from 2021-2050.

Risk is modelled using a convex combination of expected value and average value at risk, so Risk(λ, α) is

$$(1 - \lambda)\mathbb{E}[Z] + \lambda AVaR_{1-\alpha}[Z]$$

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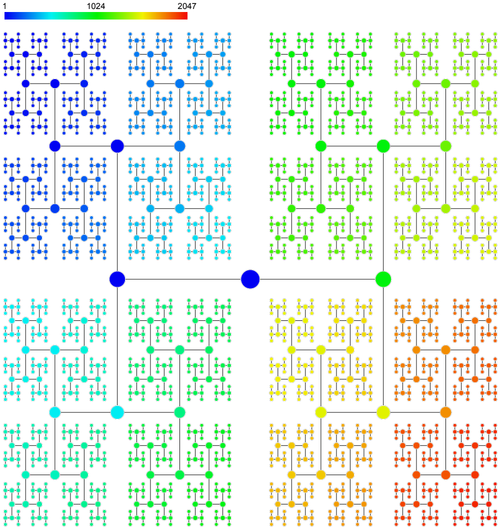

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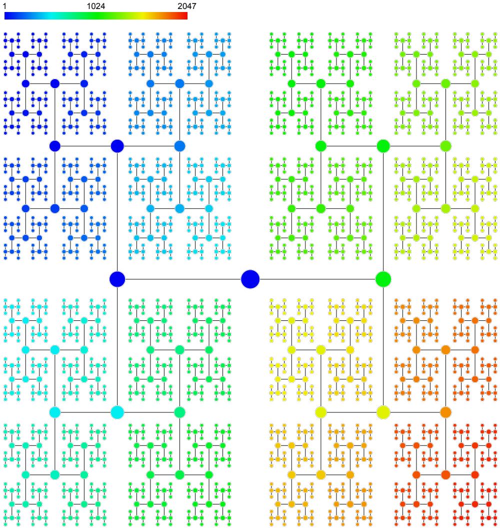

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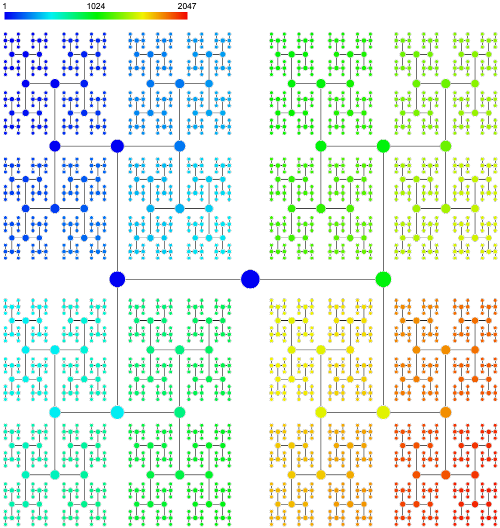

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Sets:

- seasons $t \in \mathcal{T}$;
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Parameters:

- d^b demand in load block b;
- u_k initial capacity of technology k;
- U_k maximum capacity increment of each new technology k;
- θ_k^b is the capacity factor for technology k, in load block b.

Medium-term Operational Model

Objective Functions

Subproblem at node n minimizes the operational costs of the electricity system:

$$\min \quad \sum_{t \in \mathcal{T}} \sum_{b \in \mathcal{B}_t} \Delta_b \sum_{h \in \mathcal{H}} \rho_h \sum_{k \in \mathcal{K}} (c_k + \tau e_k) g_k^{bh},$$

where Δ_b is the number of hours corresponding to load block b;
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Cost of investments over the tree:

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Medium-term operations

Subproblem constraints

Load balance:

$$\sum_{k \in \mathcal{K}} g_k^{bh} = d^b, \quad \forall b \in \mathcal{B}, h \in \mathcal{H},$$

Generation capacity:

$$0 \leq g_k^{bh} \leq \theta_k^b (u_k + x_k U_k) \quad \forall b \in \mathcal{B}_t, t \in \mathcal{T}, h \in \mathcal{H}, k \in \mathcal{K},$$

Stored hydro generation:

$$\sum_{b \in \mathcal{B}_t} g_{\text{hydro}}^{bh} \times \Delta_b = \mu_t^h \quad \forall h \in \mathcal{H}, t \in \mathcal{T},$$

Expansions:

$$x_k \in [0, 1], \quad \forall k \in \mathcal{K}, i \in \{1, \ldots, N\}.$$

EMERALD demonstration

EMERALD case study uses...

- Three regions (NI, HAY, SI).
- Four seasons with 10 load blocks each.
- 16 load growth scenarios.
- 13 historical years model seasonal hydrological inflows.
- Data based on two-stage model of NZ system.[3]

[3] Ferris & Philpott, 100% renewable electricity with storage (2019) `http://www.epoc.org.nz`.

EMERALD input data

Demand and carbon price scenarios are related

- Annual total energy demand increases from
  - Electric vehicles;
  - Industrial load;
  - Consumer load;
  - Tiwau (or replacement).
- NZ CCC CO_2-e budgets in target years are assumed.
- CO_2-e budgets affect carbon prices.
- Carbon prices affect fossil fuels and electricity prices.
- Electric vehicle demand = f(gasoline price,electricity price).

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EMERALD input data

Scenario tree for demand and carbon price

```
mytree, data = tree_with_data(myscenariotree.csv)

 n,p,EVTWh,industryTWh,consumerTWh,TiwauTWh,carbon
 1,-,0.1,8.525,27.727,5.475,50
 11,1,0.1389,10.750025,32.16332,5.475,50
 12,1,0.1389,11.50875,29.168804,5.475,50
 111,11,0.55,12.276,35.49056,5.475,200
 112,11,0.55,11.227425,28.55881,5.475,200
 121,12,0.55,13.14555,32.191047,5.475,200
 122,12,0.55,12.028775,25.897018,5.475,200
 1111,111,5,15.8565,39.566429,5.475,500
 1121,112,5,14.50955,31.802869,5.475,500
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```
JuDGE.visualize_tree(mytree, data)
```

Scenario tree

Creating the JuDGE model

```
model = JuDGEModel(mytree,
          ConditionallyUniformProbabilities,
          sub_problems,
          JuDGE_MP_Solver,
          discount_factor=0.92)
          risk=Risk(0.95,(1/16))
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Running EMERALD

Solving and producing output

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JuDGE.solve(model,termination=Termination(reltol=0.001))

resolve_subproblems(model)

solution = JuDGE.solution_to_dictionary(model)

(some code to set up custom_plots using plotly)

JuDGE.visualize_tree(mytree, solution,
custom=custom_plots)
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EMERALD results

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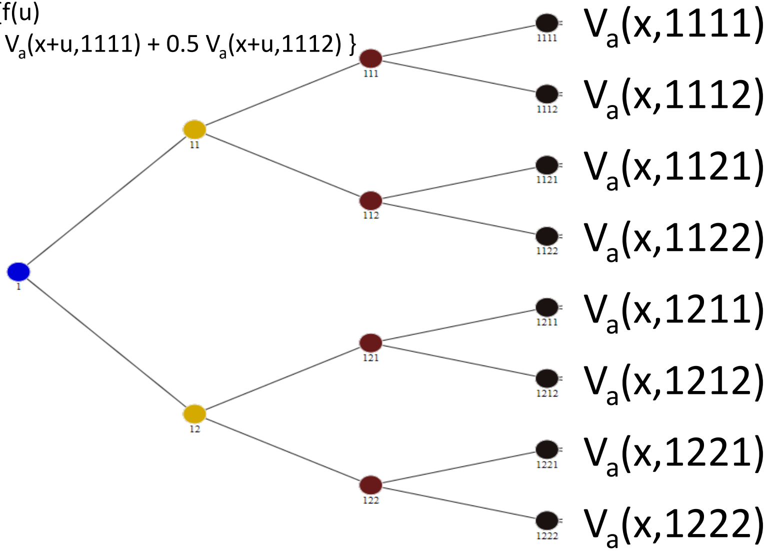
2. Agent simulation models (e.g. ENZ);
3. Deterministic planning models (e.g. GEM);
4. Stochastic, risk-averse planning models (e.g. EMERALD);

Models for optimal planning

1. Computable general equilibrium models (e.g. C-PLAN);
2. Agent simulation models (e.g. ENZ);
3. Deterministic planning models (e.g. GEM);
4. Stochastic, risk-averse planning models (e.g. EMERALD);
5. Do models (2), (3), (4) yield dynamic investment (partial) equilibrium?

Dynamic investment equilibrium by backward induction

$$V_a(x,111) = \max\{f(u) + 0.5\, V_a(x+u,1111) + 0.5\, V_a(x+u,1112)\}$$



Dynamic investment equilibrium = EMERALD

- Optimal risk-averse plan from EMERALD matches partial equilibrium when risk measures are coherent and risk-trading instruments are available.[4]
- Each agent in EMERALD has their own coherent risk measure. This corresponds to a nested risk measure with single-stage risk sets that vary with node.
- What model of social risk model should we use in EMERALD? JuDGE uses an end-of-horizon risk measure.
- NOTE: the intersection of agent risk sets define a nested risk measure for the social planner that might not be an end-of-horizon measure.

[4] Ralph & Smeers, SIOPT, 2015, Ferris & P., Operations Research, 2022.

The End

`JuDGE.jl` Julia Library downloadable from

`https://github.com/EPOC-NZ/JuDGE.jl`

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