

Renewable energy capacity planning using JuDGE

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(joint work with Anthony Downward)

Modelling approaches for electricity investment

- 1 System dynamics with market agents (ENZ).
 - specify policy settings (taxes, incentives, constraints) and then simulate agent's actions.
 - actions can anticipate future outcomes of a scenario (e.g. to estimate NPV).
 - actions typically ignore competitive response.
 - misrepresent the social cost of meeting objectives.
- 2 Social investment planning (GEM)
 - optimize social welfare using a (stochastic) mixed integer program.
 - gives minimum-cost plan to meet social objectives e.g. 100% renewable electricity.
 - not consistent with market forces; plans appear to ignore competition between agents.

Modelling approaches for electricity investment

① How to combine **planning** and **market**?

Theorem

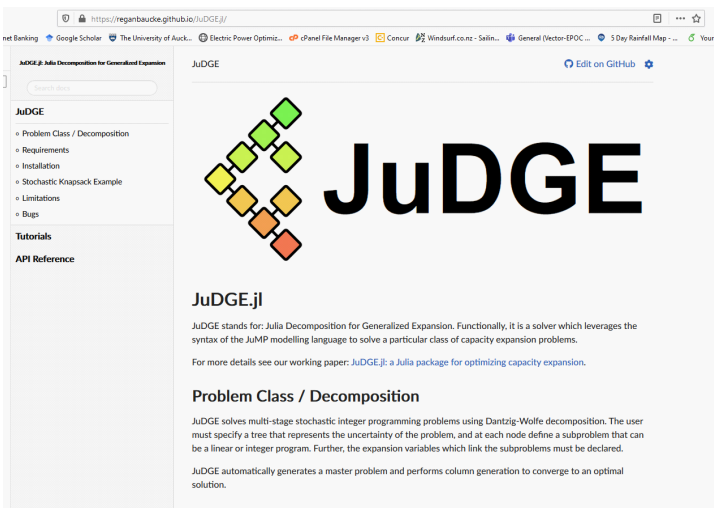
If markets are competitive, convex and complete, and agents optimize using similar coherent risk measures, then partial equilibrium of the electricity market dynamic investment game is the same as the solution to a risk averse dynamic stochastic optimization problem (social planning problem).

② Open question: how to deal with an incomplete market for risk.

Competitive and complete market

- Where, when, how big to build capacity?
- Multistage stochastic optimization.
- Uncertainty at different time scales.
- Multi-horizon scenario trees.

<https://reganbaucke.github.io/JuDGE.jl/>



The screenshot shows the homepage of the JuDGE project. The browser address bar displays `https://reganbaucke.github.io/JuDGE.jl/`. The page title is "JuDGE" with an "Edit on GitHub" link. A navigation sidebar on the left includes sections for "JuDGE" (with sub-items: Problem Class / Decomposition, Requirements, Installation, Stochastic Knapsack Example, Limitations, Bugs), "Tutorials", and "API Reference". The main content area features a logo of a diamond-shaped grid of colored squares (green, yellow, orange, red) to the left of the large text "JuDGE". Below the logo, the text "JuDGE.jl" is followed by a paragraph explaining that JuDGE stands for Julia Decomposition for Generalized Expansion and is a solver for capacity expansion problems. A link to a working paper is provided. The "Problem Class / Decomposition" section explains that JuDGE solves multi-stage stochastic integer programming problems using Dantzig-Wolfe decomposition. A final paragraph states that JuDGE automatically generates a master problem and performs column generation to converge to an optimal solution.

JuDGE = Julia Decomposition for Generalized Expansion

Summary

- 1 Introduction
- 2 An example problem: Emerald
- 3 The stage problem in Emerald
- 4 Results
- 5 Other features of JuDGE
- 6 Extensions
- 7 A better model for dry years

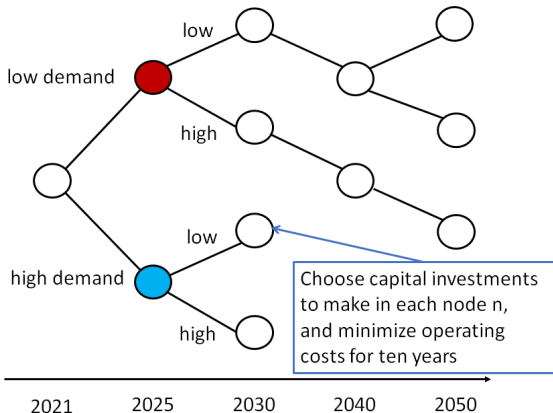
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Emerald: Planning for a net-zero carbon economy

- Increase capacity of NZ electricity system to meet **increased demand** by 2050.
- Scenario tree models states of the world with changes in **EV demand, industrial load, government policy e.g. emission prices**.
- Each subproblem computes optimal operation of electricity system in state of the world.
- State of the world lasts 4,5,10,10,10 years (giving 5 stages) and involves **hydro** inflow and **wind** uncertainty.
- Example model has 2 branches per stage giving 31 nodes (16 scenarios).

Multihorizon scenario tree



Multihorizon scenario tree for electricity expansion model. In each node of the tree we solve a two-stage operational subproblem given investments in capacity up to this time. The scenario tree for this subproblem is suppressed.

Emerald representation of demand uncertainty

emeraldtreeC50.csv - Saved

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L8

	A	B	C	D	E	F	G	H	I
1	n	p	evgrowth	phgrowth	loadgrowth	smelter	carbon		
2	1	-	1.000	1.000	1.000	1	50		
3	11	1	1.389	1.281	1.190	1	50		
4	12	1	4.917	1.890	1.052	0	50		
5	111	11	5.500	1.440	1.280	1	50		
6	112	11	7.156	1.317	1.030	0	50		
7	121	12	19.470	2.159	1.161	0	50		
8	122	12	25.333	1.975	0.934	0	50		
9	1111	111	86.389	1.860	1.427	1	50		
10	1112	111	22.012	1.623	1.546	1	50		
11	1121	112	112.405	1.702	1.147	0	50		
12	1122	112	28.641	1.485	1.243	0	50		
13	1211	121	305.817	2.789	1.294	0	50		
14	1212	121	77.823	2.433	1.402	0	50		
15	1221	122	387.912	2.551	1.041	0	50		
16	1222	122	101.389	2.225	1.127	0	50		
17	11111	1111	186.111	2.284	1.450	1	50		
18	11112	1111	141.062	2.062	1.719	1	50		
19	11121	1112	47.421	1.992	1.571	1	50		
20	11122	1112	35.943	1.799	1.883	1	50		
21	11211	1121	242.158	2.089	1.166	0	50		
22	11212	1121	183.543	1.886	1.382	0	50		
23	11221	1122	61.702	1.823	1.263	0	50		
24	11222	1122	46.767	1.645	1.498	0	50		
25	12111	1211	658.833	3.424	1.315	0	50		
26	12112	1211	499.361	3.091	1.559	0	50		
27	12121	1212	167.872	2.987	1.424	0	50		
28	12122	1212	127.238	2.696	1.689	0	50		
29	12211	1221	857.239	3.132	1.057	0	50		
30	12212	1221	649.742	2.827	1.254	0	50		
31	12221	1222	218.426	2.732	1.145	0	50		
32	12222	1222	165.556	2.467	1.358	0	50		
33									

emeraldtreeC50

Ready 75%

Input file for scenario tree

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Subproblem n is a MIP

$$\begin{aligned}
 SP(n): \quad \min \quad & \langle \pi_n^+, x^+ \rangle - \langle \pi_n^-, x^- \rangle - \mu_n \\
 & + \sum_t \mathbb{E}[Z(t, \omega)] \\
 \text{s.t.} \quad Z(t, \omega) = & \sum_{b \in t} H(b) \sum_k C_k y_k(t, \omega, b) \\
 & + \sum_{b \in t} H(b) Rq(t, \omega, b), \\
 z_k \leq & u_k + x_k^+ U_k - x_k^- V_k, \\
 y_k(t, \omega, b) \leq & \mu_k(t, \omega, b) z_k, \\
 \sum_{b \in t} H(b) y_k(t, \omega, b) \leq & v_k(t, \omega) \sum_{b \in t} H(b) z_k \\
 & + s(t-1, \omega) - s(t, \omega), \\
 q(t, \omega, b) \leq & d(t, \omega, b), \\
 d(t, \omega, b) \leq & \sum_k y_k(t, \omega, b) + q(t, \omega, b), \\
 z, y, q, s, S \geq & 0, \\
 x^+, x^- \in & \{0, 1\}^K.
 \end{aligned}$$

Subproblem n is a MIP

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 & + \sum_{b \in t} H(b) R q(t, \omega, b), \\
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 z_k \leq & u_k + x_k^+ U_k - x_k^- V_k, \\
 y_k(t, \omega, b) \leq & \mu_k(t, \omega, b) z_k, \\
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Some results from Emerald

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Other features of JuDGE

- Open source using JuMP.
- Can model **time lags** from investment to deployment.
- Can model **risk** .
- Can use binary variables to model **discrete investments** (computes MIP solution using branch-and-price).

Modeling risk

- JuDGE can model **social planner** risk aversion over the scenario tree using the end-of-horizon risk measure

$$\rho(Z) = (1 - \lambda)\mathbb{E}[Z] + \lambda\text{CVaR}_{1-\alpha}[Z]$$

where $Z(n)$, $n \in \mathcal{L}$, measures accumulated losses along each path from the root node to $n \in \mathcal{L}$. CVaR is the **conditional value at risk** of the loss distribution (the expected value of the worst 100 α % of losses).

- JuDGE can also model **agent** risk aversion within a node problem e.g. for investment and operation over next ten years.
- We can make the risked positions of agents and planner align if markets for risk are **complete**.

Incomplete markets for risk?

- Leader: Government sets taxes, regulations, incentives
- Followers: Private investors respond with investments in competitive risked equilibrium.
- Question: How bad can the equilibrium be? We can compute the risked equilibrium for each scenario-tree node using JuDGE.

Conclusion

- JuDGE package available for free at <https://github.com/reganbaucke/JuDGE.jl>.
- Stochastic capacity expansion via **decomposition** enables problems to be solved at realistic scale.
- We are developing better models for wind that reflect time variation based on representative days.

Conclusion

THE END

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References

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Application: Planning for a net-zero carbon economy

Recommendation 1

Emissions budget levels

We recommend the Government set and meet the emissions budgets as outlined in the table below. These emissions budgets are expressed using GWP₁₀₀ values from the IPCC's *Fifth Assessment Report (AR5)* for consistency with international obligations relating to Inventory reporting.

	2019	Emissions budget 1 (2022 - 2025)	Emissions budget 2 (2026 - 2030)	Emissions budget 3 (2031 - 2035)
All gases, net (AR5)		290 MtCO ₂ e	312 MtCO ₂ e	253 MtCO ₂ e
Annual average	78.0 MtCO ₂ e	72.4 MtCO ₂ e/yr	62.4 MtCO ₂ e/yr	50.6 MtCO ₂ e/yr

New Zealand CO₂ emission budgets (NZCCC May 31, 2021).

Branch and price

In many instances the optimal solution to the LP relaxation of the master problem has **naturally binary** solutions. When this is **not** the case JuDGE can either:

- stop generating columns, and solve the master problem as a MIP, or
- perform a **branch-and-price** procedure that generates new columns after branching on master variables.

Investment lags

- Investment in node n occurs by default after information on state n is revealed.
- In practice, investment availability **lags** investment decision i by at least δ_i stages.
- Use a set of $m \times m$ diagonal matrices $L(h, n)$ where

$$L(h, n)_{ii} = \begin{cases} 1 & \text{if } n \text{ lags } h \text{ by at least } \delta_i \\ 0 & \text{otherwise} \end{cases}$$

giving RMP constraint

$$- \sum_{j \in \mathcal{J}_n} \hat{z}_n^+(j) w_n(j) \geq - \sum_{h \in \mathcal{P}_n} L(h, n) x_h^+, \quad n \in \mathcal{N}.$$

- JuDGE enables lags and investment durations to be specified.

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How to represent dry years?

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 s(t, \omega) \in & [S(t) - \delta, S(t) + \delta], \\
 q(t, \omega, b) \leq & d(t, \omega, b), \\
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