Multi-horizon modelling for 100%-renewable investment planning

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Joint work with Andy Philpott

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THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

Outline

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Background

- Multi-horizon stochastic programming
- Implementation and communication of policies

Multi-horizon modelling framework

Medium-term Operational Model

Long-term Planning Model

EMERALD Output

Background

Multi-horizon planning

The concept of multi-horizon modelling is the idea that you are planning for across multiple time-horizons at once (short-term, medium-term, and long-term) and are explicitly accounting for how strategic, tactical and operational decisions influence each other.

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In the short-term, we have operational decisions that result in immediate costs and revenue; however, at the same time the decision maker is considering capacity expansion decisions that will lead to lower operational costs, or higher revenue in the future.

Background

Implementation and communication of policies

Stochastic programming has been promoted in academia for decades, but has only recently been gaining traction in capacity planning settings within business.

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In part, the delay in acceptance has been due to the limitations in the size of problems that could be modelled, but more significantly the solution to a stochastic program is a policy that adapts to information as it is revealed, and this has been difficult communicate to decision makers.

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The concept of Dynamic Adaptive Pathways has made in-roads in areas where there is deep uncertainty, particularly climate change planning.[2] This, however, is typically more qualitative than quantitative.

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- allows users to easily implement multi-horizon optimization models using the JuMP modelling language;

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- outputs an interactive view of the results over the scenario tree, enabling decision makers explore the optimal policy.

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Multi-horizon modelling framework

What type of problems can be modelled in JuDGE?

JuDGE is a Julia/JuMP-based package that facilitates the modelling of multi-horizon stochastic capacity planning problems.

- $\mathcal{N}$ is the set of nodes in the scenario tree;
- ϕ_n the probability of the state of the world n occurring;
- $\mathcal{P}_n$ the set of nodes on the path to (and including) node n;
- m is the number of expansion variables;
- $z_n \in \mathcal{Z}_+^m$ are the variables for the expansions made at node n;
- y_n is the variable vector for stage-problem n;
- $\mathcal{Y}_n$ is the stage-problem feasibility set.

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\min_{y,z} \quad & \sum_{n\in\mathcal{N}} \phi_n (c_n^\top z_n + q_n^\top y_n) \\
\text{s.t.} \quad & A_n y_n \leq b + D \sum_{h\in\mathcal{P}_n} z_h, && \forall n \in \mathcal{N}, \\
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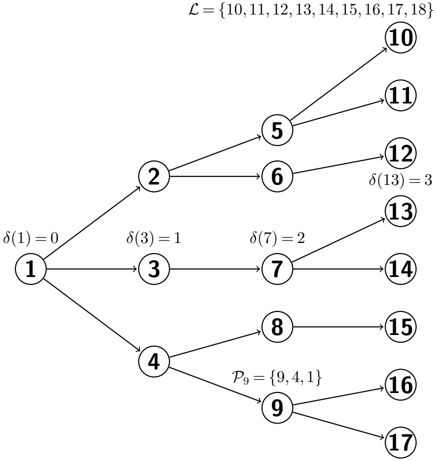

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JuDGE applies Dantzig-Wolfe decomposition to the problem by automatically constructing a master problem that handles the investment decisions, and generates columns from the nodal subproblems.

These columns' costs are the operational costs of the nodal subproblems, and the columns' coefficients are the utilized investments.

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\text{s.t.} \quad & \sum_{j\in\mathcal{J}_n} \hat{z}_n^j w_n^j \le \sum_{h\in\mathcal{P}_n} x_h, \ \forall n \in \mathcal{N}, \\
& \sum_{j\in\mathcal{J}_n} w_n^j = 1, \qquad \forall n \in \mathcal{N}, \\
& w_n^j, x_n \ge 0, \quad \forall n \in \mathcal{N}, j \in \mathcal{J}_n.
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The columns are indexed $j \in \mathcal{J}_n$ for each node n, and added to the restricted master problem, with cost ψ_n^j and coefficients $\hat{z}_n^j$.

This problem seeks to choose investments x that minimize the total expected cost, given the columns that have been generated.

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This problem is solved without any integer variable restrictions, since dual variables are needed for the column generation process.

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

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The parameters are:

- d^b demand in load block b;
- u_t initial capacity of technology t;
- U_t capacity of each new unit of technology t; and
- θ_t^b is the capacity factor for technology t in load block b.

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Hydro availability:

$$\sum_{b \in B} g_{\text{hydro}}^{bh} \times \Delta_b \leq \mu^h \quad \forall h \in \mathcal{H},$$

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Objective Functions

The objective function of the nodal subproblem is to minimize the operational costs of the electricity system:

$$\min \quad \sum_{b\in\mathcal{B}} \Delta_b \sum_{h\in\mathcal{H}} \rho_h \sum_{t\in\mathcal{T}} (c_t + \tau e_t) g_t^{bh},$$

where Δ_b is the number of hours corresponding to load block b;
ρ_w is the probability of hydrological year h;
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Due to the decomposition, we must separately account for the cost of investments over the tree:

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$$\min \quad \sum_{n \in \mathcal{N}} \phi_n \sum_{t \in \mathcal{T}} C_t x_t,$$

where ϕ_n is the probability of reaching node n, and C_t is the capital cost (per unit) of technology t, and x_t represents the investment decision for technology t in the master problem.

Medium-term Operational Model

Objective Functions

The objective function of the nodal subproblem is to minimize the operational costs of the electricity system:

$$\min \quad \sum_{b\in\mathcal{B}} \Delta_b \sum_{h\in\mathcal{H}} \rho_h \sum_{t\in\mathcal{T}} (c_t + \tau e_t) g_t^{bh},$$

where Δ_b is the number of hours corresponding to load block b;
ρ_w is the probability of hydrological year h;
c_t is the marginal cost of technology t;
e_t gives the emissions factor of technology t; and
τ is the carbon tax.

Due to the decomposition, we must separately account for the cost of investments over the tree:

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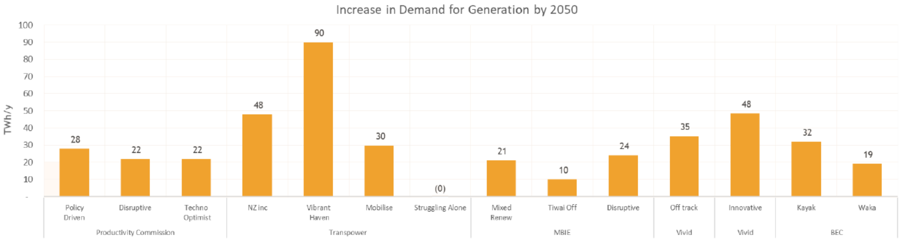
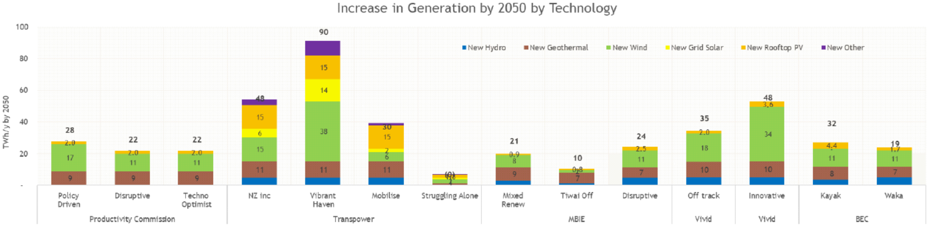
Outline

Scenarios for the future

What investments should be made?





14 scenarios for electricity demand and generation mix in 2050.

There are 14 different ‘optimal’ plans: which should be implemented, if any?

Demand scenarios

The annual demand (TWh) is a stochastic process, modelled using a scenario tree.

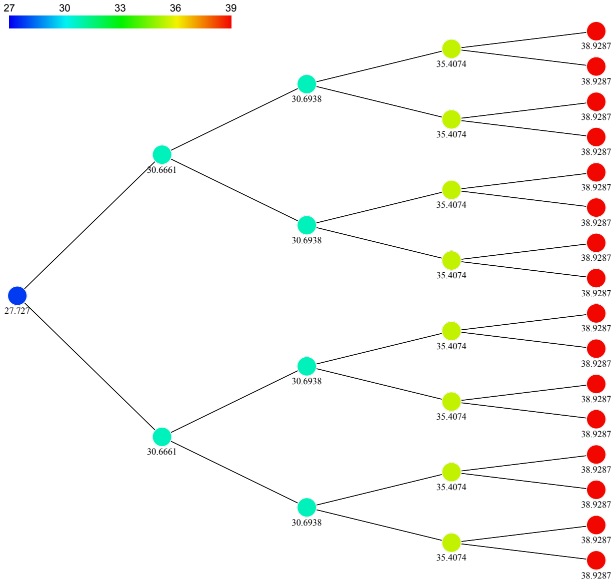
Consumer demand

Industrial demand

Electric Vehicle demand

Tiwai Point Smelter demand

Total demand



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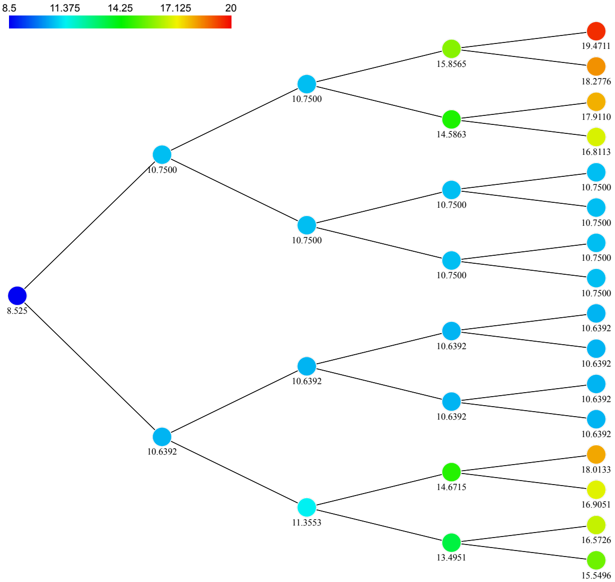

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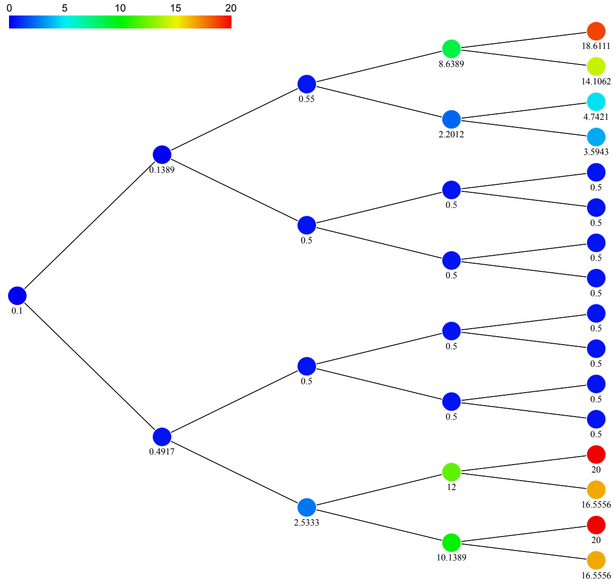

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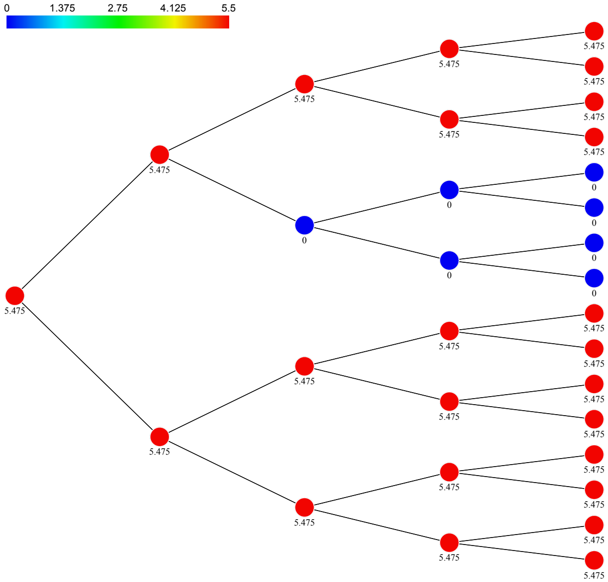

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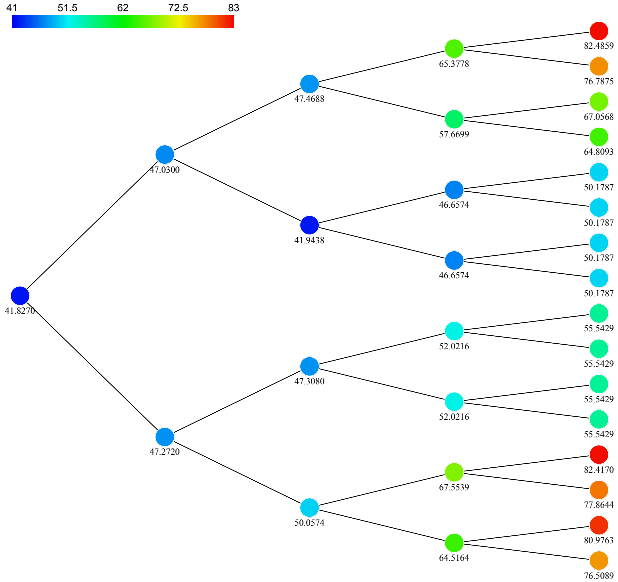

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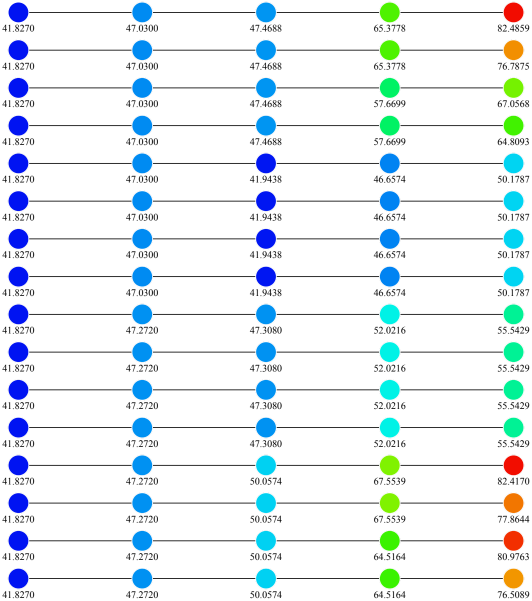

Multi-horizon modelling

Creating and solving the JuDGE Model

Once a tree has been created, and a function declared which defines the nodal subproblems, we can create a `JuDGEModel` as follows:

```
model = JuDGEModel(tree, ConditionallyUniformProbabilities,
        sub_problems,optimizer_with_attributes((method=GLPK.INTERIOR)
        -> GLPK.Optimizer(), "msg_lev" => 0, "mip_gap" => 0.0)
        risk = Risk(0.25,0.1))
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```

If the model passes the in-built testing, ensuring that the JuMP models are set up correctly, the model can be solved using the command:

```
JuDGE.solve(model, Termination = termination(reltol=1e-4)
```

Outline

Communication of JuDGE Solutions

Visualizing the policy

One of the challenges with stochastic multi-horizon optimization is the communication of an optimal policy.

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JuDGE provides a custom framework to interactively explore the policy, enabling users to understand how the revelation of information influences the investment decisions, but also how these, in turn, affect the operational decisions in the short-term.

Communication of JuDGE Solutions

Visualizing the policy

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JuDGE provides a custom framework to interactively explore the policy, enabling users to understand how the revelation of information influences the investment decisions, but also how these, in turn, affect the operational decisions in the short-term.

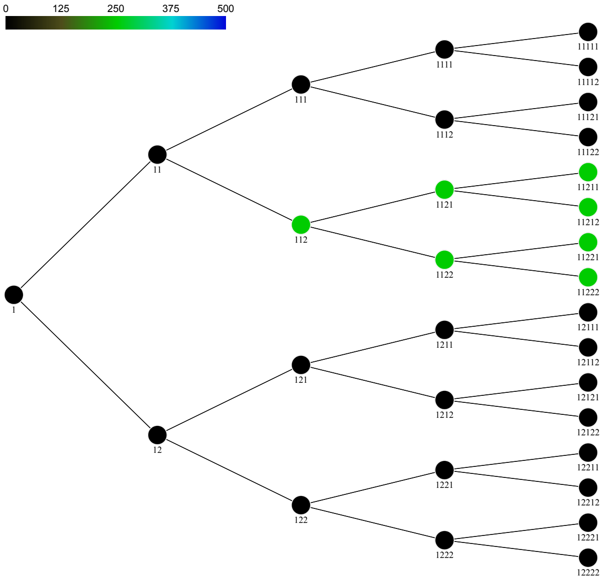
This framework is built around html and javascript, and therefore is very flexible, with the ability to integrate: maps, plots, svg graphics, or any other web-based visualization.

Coal Rankine shutdown

There are two 250MW coal-powered Rankine units near Auckland. These have an O & M cost of $70,000 / MWyr.

EMERALD will time the closure of these plants along with investment in other generation technologies.

Scenario:
No Batteries
No EV smart charging
CO_2 charge $50/$TCO_2$e



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Scenario:
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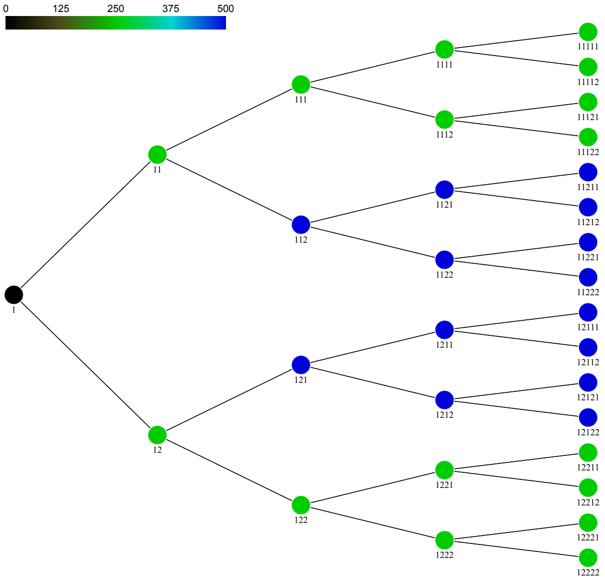
No EV smart charging
CO_2 charge $600/$TCO_2$e by 2050



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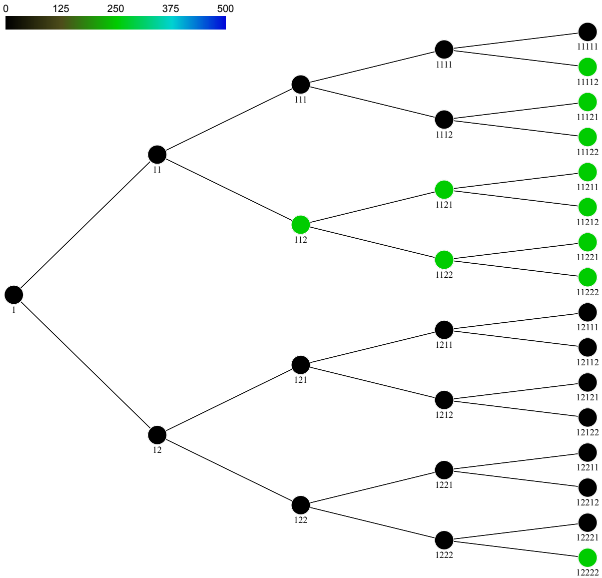

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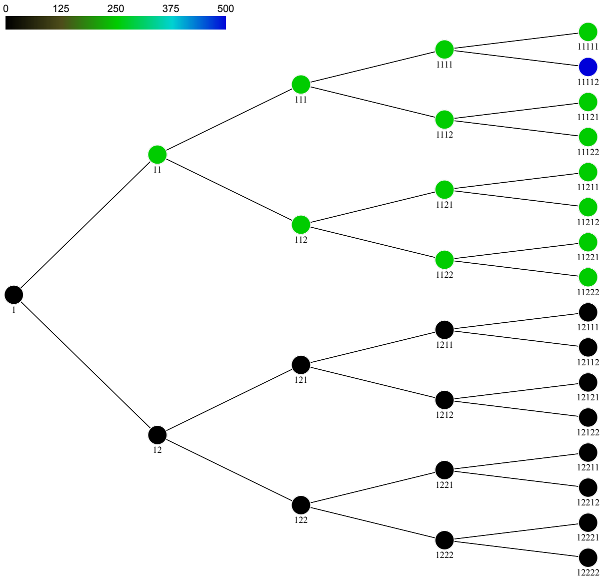

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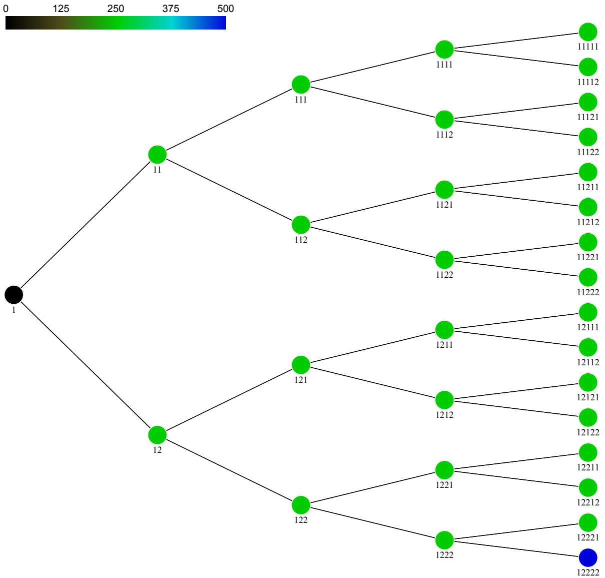

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Scenario:
Batteries
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CO_2 charge \$150/TCO_2e by 2050

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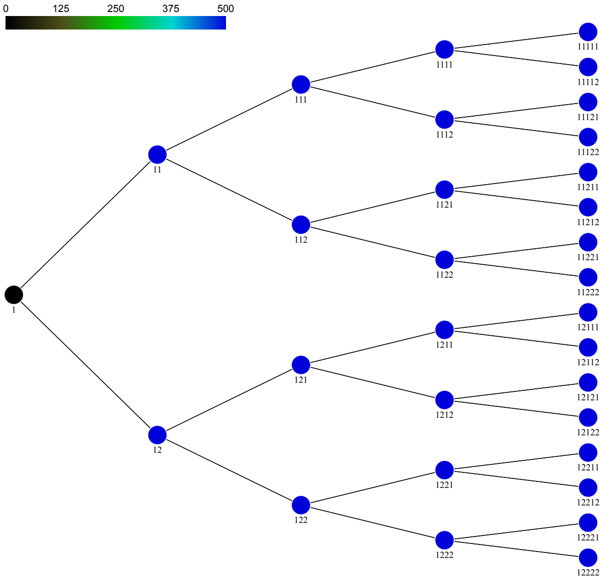
Scenario:
Batteries
EV smart charging
CO_2 charge $600/T$CO_2$e by 2050



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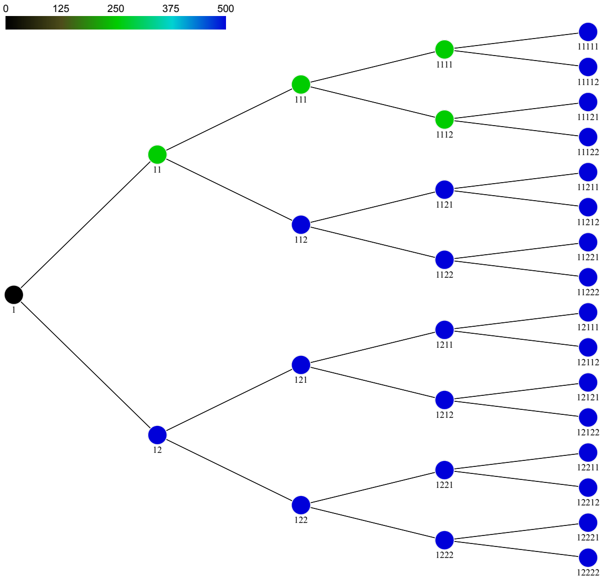
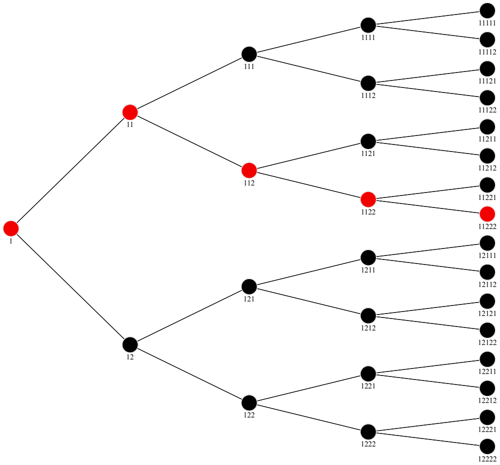
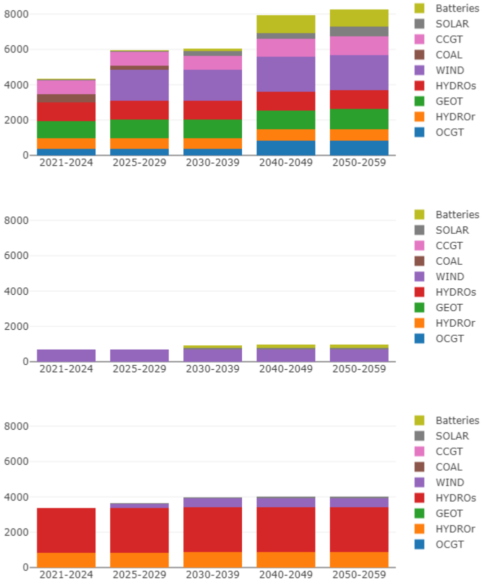
Scenario:
Batteries
EV smart charging
CO_2 charge $600/T$CO_2$e by 2050
Risk averse



Optimal capacity mix

Risk-neutral solution





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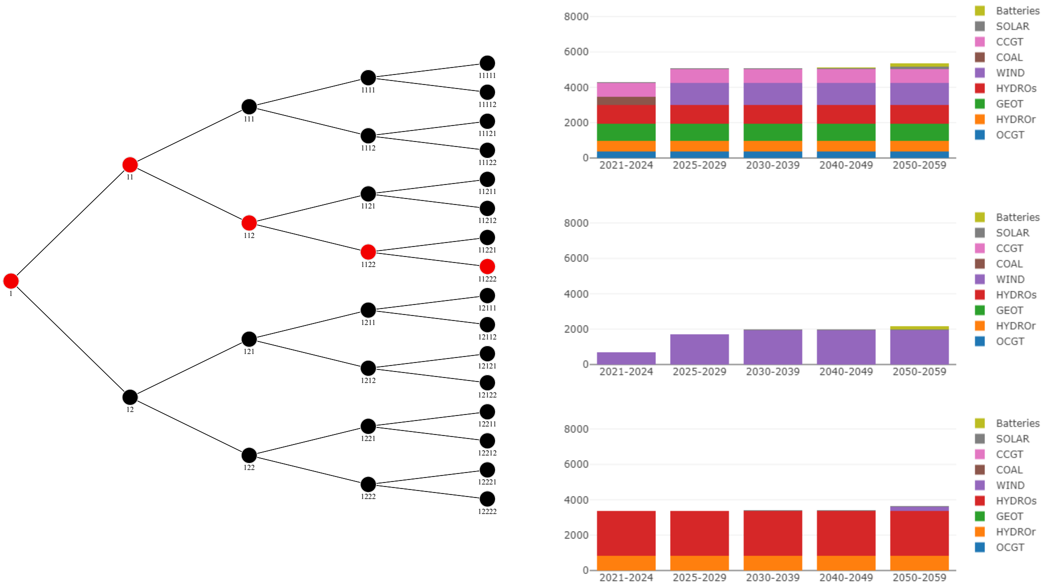
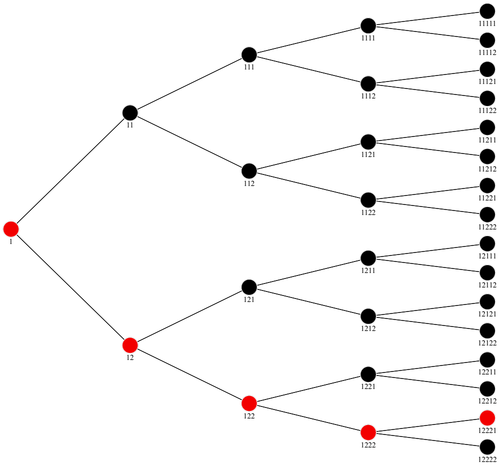
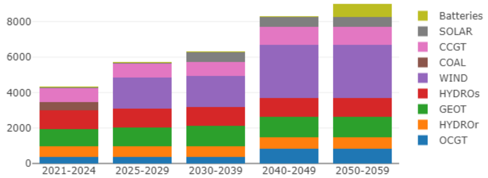
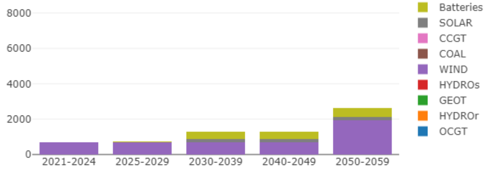


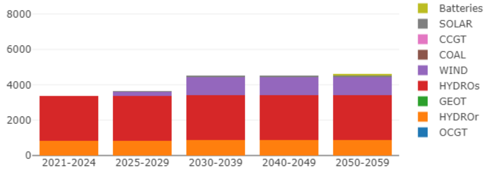
Optimal capacity mix

Risk-neutral solution









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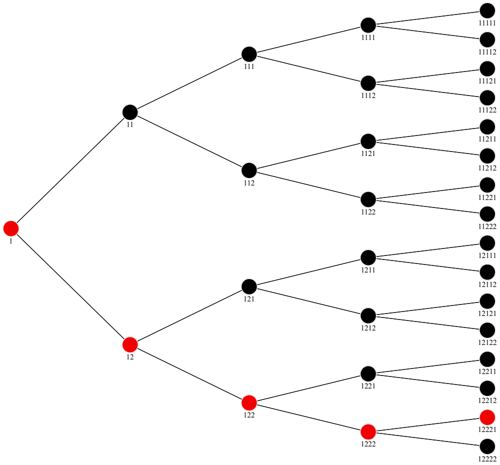
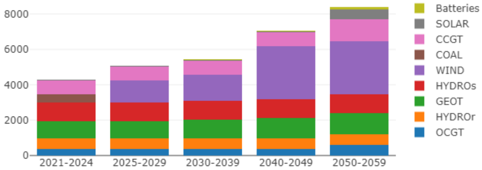
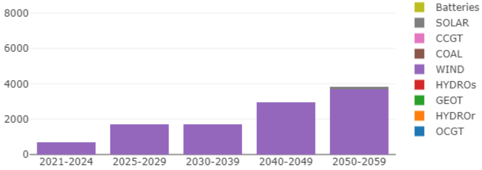
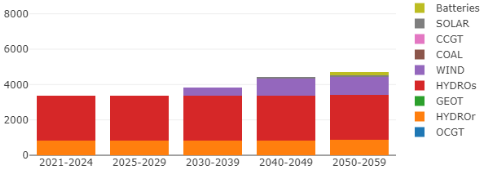


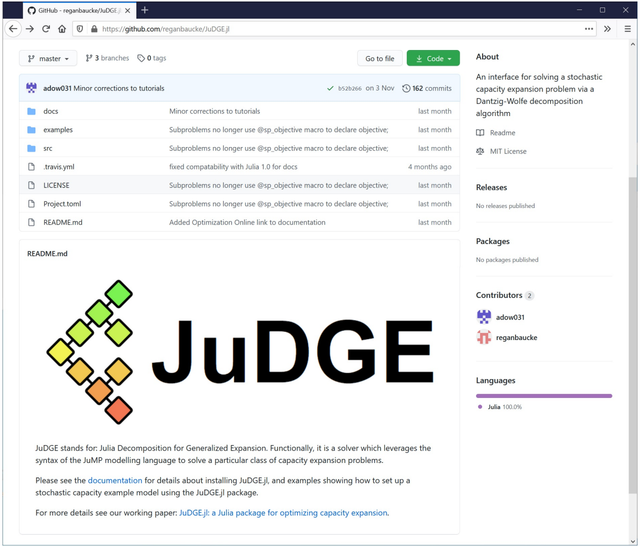






Installing and using JuDGE

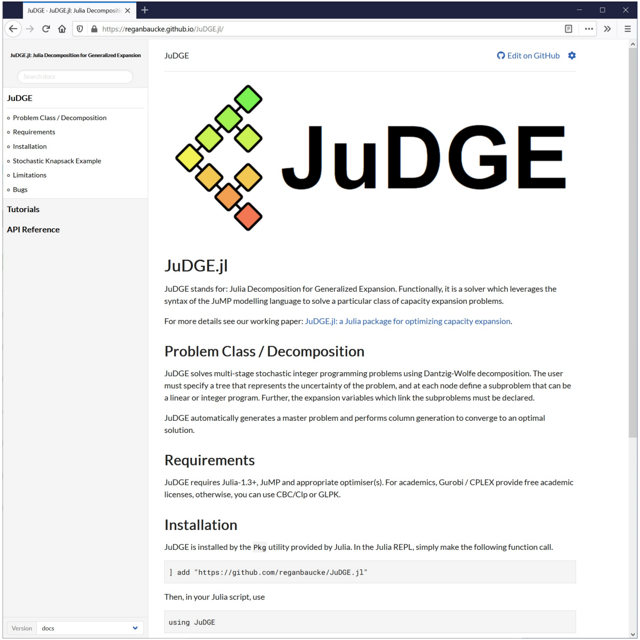
Github Repository



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

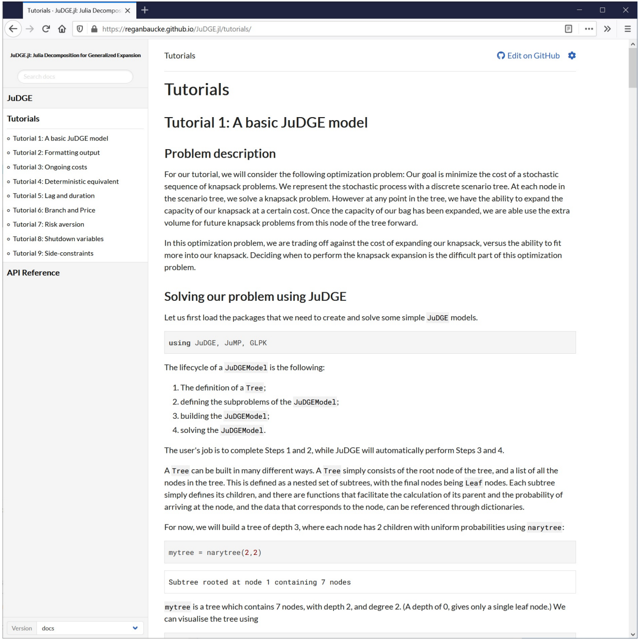
Installing and using JuDGE

Installing the JuDGE Package



Installing and using JuDGE

Tutorials and Examples



Tutorials · JuDGE.jl: Julia Decompos

https://reganbaucke.github.io/JuDGE.jl/tutorials/

JuDGE.jl: Julia Decomposition for Generalized Expansion

Search docs

JuDGE

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Tutorials

Tutorial 1: A basic JuDGE model

Problem description

For our tutorial, we will consider the following optimization problem: Our goal is minimize the cost of a stochastic sequence of knapsack problems. We represent the stochastic process with a discrete scenario tree. At each node in the scenario tree, we solve a knapsack problem. However at any point in the tree, we have the ability to expand the capacity of our knapsack at a certain cost. Once the capacity of our bag has been expanded, we are able use the extra volume for future knapsack problems from this node of the tree forward.

In this optimization problem, we are trading off against the cost of expanding our knapsack, versus the ability to fit more into our knapsack. Deciding when to perform the knapsack expansion is the difficult part of this optimization problem.

Solving our problem using JuDGE

Let us first load the packages that we need to create and solve some simple `JuDGE` models.

```
using JuDGE, JuMP, GLPK
```

The lifecycle of a `JuDGEModel` is the following:

1. The definition of a `Tree`;
2. defining the subproblems of the `JuDGEModel`;
3. building the `JuDGEModel`;
4. solving the `JuDGEModel`.

The user's job is to complete Steps 1 and 2, while JuDGE will automatically perform Steps 3 and 4.

A `Tree` can be built in many different ways. A `Tree` simply consists of the root node of the tree, and a list of all the nodes in the tree. This is defined as a nested set of subtrees, with the final nodes being `Leaf` nodes. Each subtree simply defines its children, and there are functions that facilitate the calculation of its parent and the probability of arriving at the node, and the data that corresponds to the node, can be referenced through dictionaries.

For now, we will build a tree of depth 3, where each node has 2 children with uniform probabilities using `narytree`:

```
mytree = narytree(2,2)
```

```
Subtree rooted at node 1 containing 7 nodes
```

`mytree` is a tree which contains 7 nodes, with depth 2, and degree 2. (A depth of 0, gives only a single leaf node.) We can visualise the tree using

Thanks for your attention.

Any questions?

`JuDGE.jl` Julia Library `https://github.com/EPOC-UoA/JuDGE.jl`

Contact me: `a.downward@auckland.ac.nz`