Stochastic Models for Generation Unit Commitment

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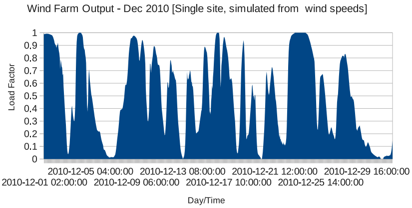
Agenda

- Motivation
- Day-Ahead and Intraday Stochastic Models
- Forecast & Scenario Simulation
- Rolling Horizon Evaluation
- The GB Model
- Results
- Conclusions

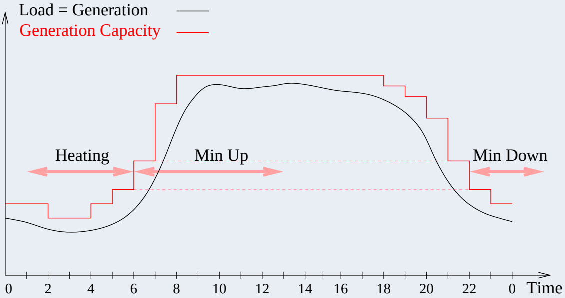
Our Motivation - Wind Power Uncertainty

- Increasing supply from volatile renewable sources → predictability problem
- Installed Wind in UK 2012: 6.5GW → predicted 2020: 28GW
- In this context, how does day-ahead UC compare to intraday UC?
- What is the added value of stochastic models over deterministic ones?



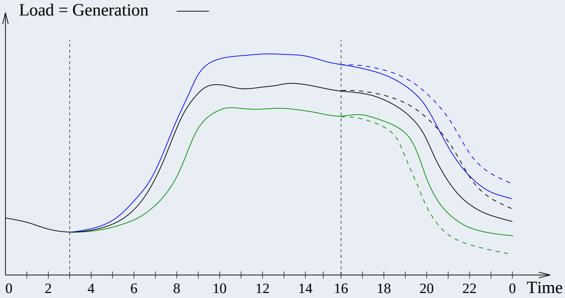
Deterministic Unit Commitment Problem

- Minimum cost on/off (binary) and power output decisions (24h)
- Constraints: load balance, spinning reserve, generator bounds, up/downtimes, ramp rates
- Large MIP, solved e.g. by B&C



Stochastic Unit Commitment Problem

- Wind forecast error is captured by including a variety of scenarios
- Multiple wind scenarios result in different residual loads – “spread” increases over time, as forecast uncertainty increases
- Additional constr.: non-anticipativity, startup notification time

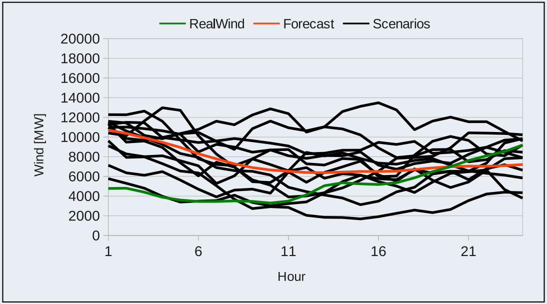


Day-Ahead vs. Intraday Planning: Overview

- UC procedures vary from one operator to another
- Day-ahead example: prepare a 24h schedule between noon and 4pm, schedule becomes active at midnight
- Intraday example: make 24h schedules, update them every 1-3 hours
- Different types of stochastic models: two-stage and multi-stage

Stochastic Day-Ahead Model

- Two-stage stochastic model with 12 wind scenarios
- Forecasts are made well in advance (here: 8h)
- Scenarios are independent, i.e. don't form a tree
- Non-Anticipativity: common commitments in all scenarios, except OCGT and pumped storage



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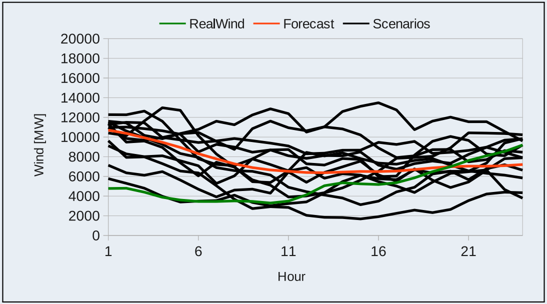
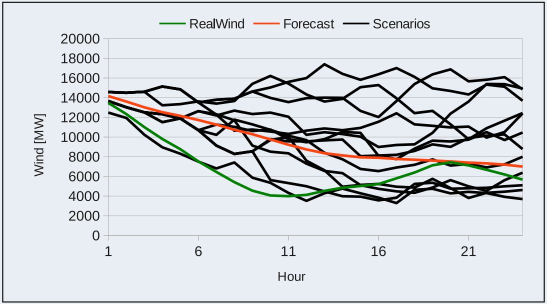


Stochastic Intraday Model

- Multistage stochastic model with 12 wind scenarios
- Forecasts are made shortly beforehand (here: 1h)
- Scenarios are organised in a tree structure
- Non-Anticipativity: identical solutions in scenario bundles, identical commitments on first stage, respect startup notification times



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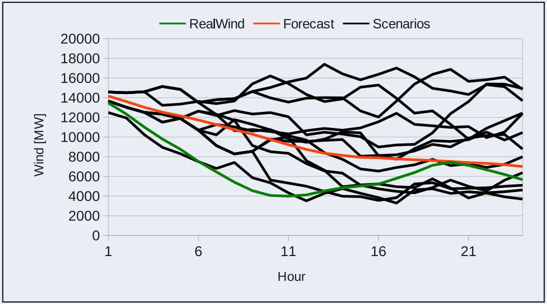

Forecast & Scenario Simulation: Overview

- Required:
  - historic wind data
  - historic point forecasts
  - scenarios
- Available:
  - historic regional wind speeds [3]
  - scenario generation techniques for forecast errors [6, 2]
- Point forecasts need to be synthesized

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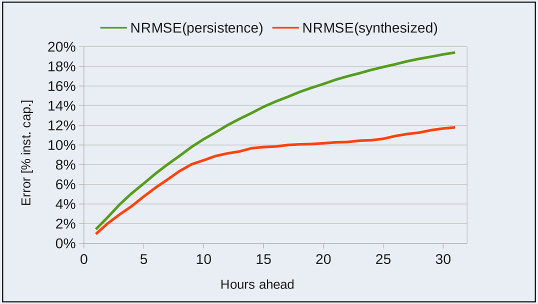
Synthesizing Point Forecasts

- State of the art wind power forecasts combine NWP and TS models [4]
- Synthesized forecasts should match their error statistics [1]
- Step 1: Synthesize forecasts by matching average past wind patterns
- Step 2: Pattern forecasts are unreliable ≥6h ahead → use weighted average of pattern forecast and shifted real wind as final forecast



Forecast error statistics of synthesized forecasts for the year 2010.

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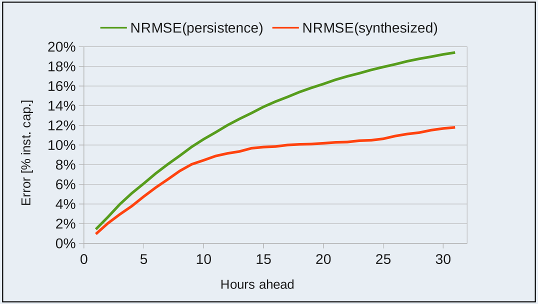

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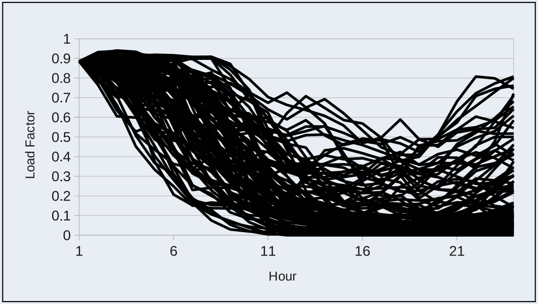
Scenario Simulation and Selection

1. Once point forecasts are available, fit correlated $ARMA(1,1)$ models to regional error time series [6]
2. Simulate 500+ error scenarios
3. Add errors to point forecasts, translate wind speeds to load factors
4. Select scenarios and merge into a tree if required [2]



Example selecting six scenarios in the region North Wales.

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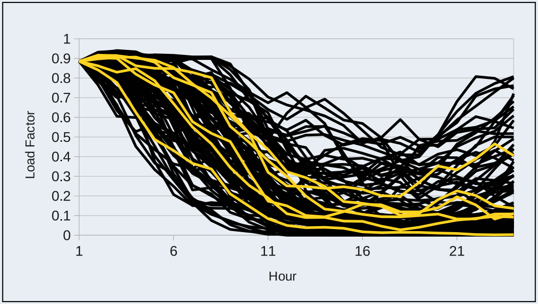


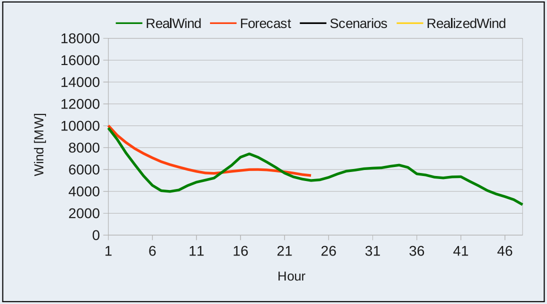
Example selecting six scenarios in the region North Wales.

Rolling Horizon Evaluation: Overview

- Compare deterministic vs. stochastic models in both, the day-ahead and intraday UC context
- Long term rolling horizon evaluation: define the procedure

Rolling Evaluation: The Intraday Procedure

- Use the wind forecast from one hour ago, solve deterministic model
- . . . or a stochastic model. Fix first stage commitments.
- Realize three hours of real wind, adapt OCGT, PS, shed load, remaining reserve. Beyond three hours use the next forecast.
- Roll three hours forward and repeat.



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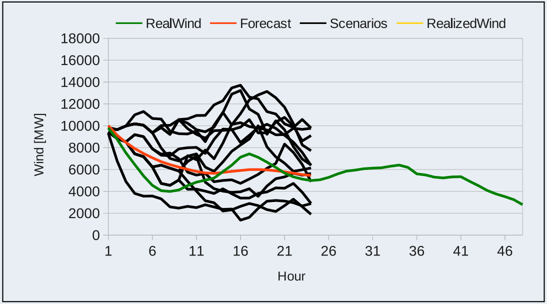

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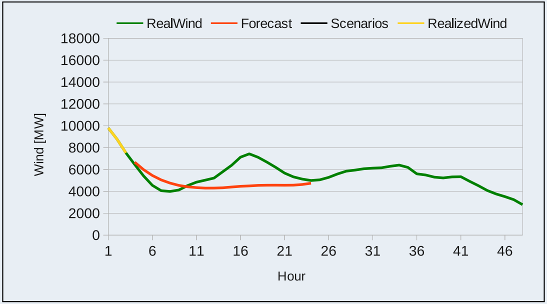

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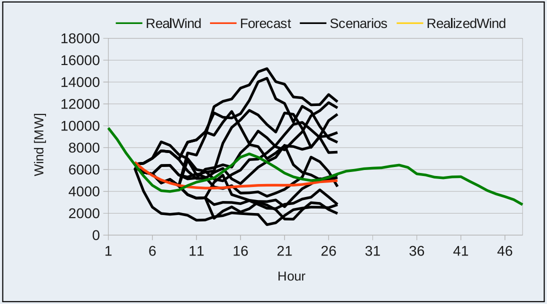

Rolling Evaluation: The Day-Ahead Procedure

- Use wind forecast from eight hours ago, solve det./stoch. model
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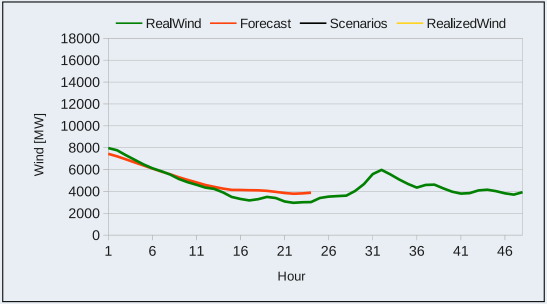

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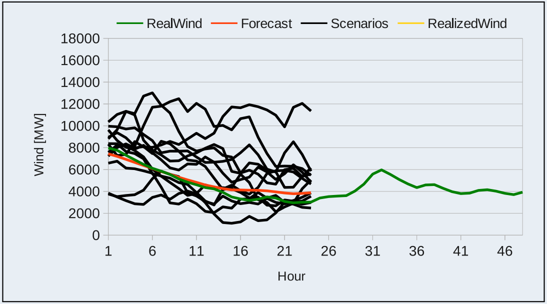

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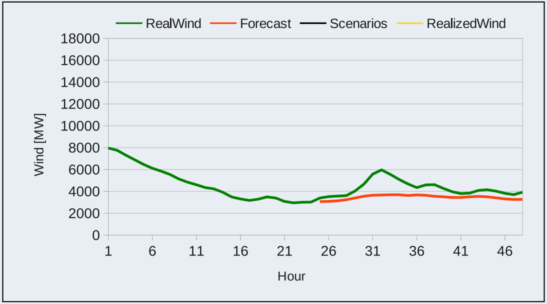

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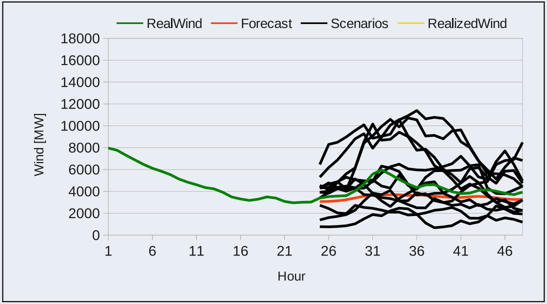

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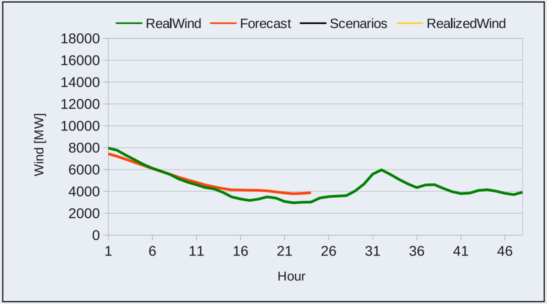

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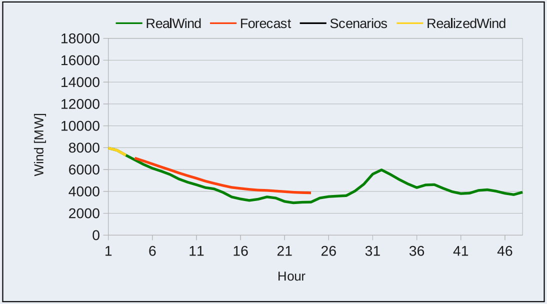

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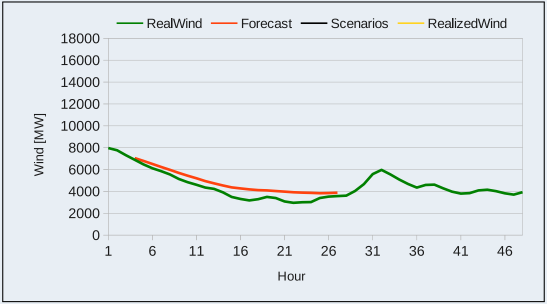
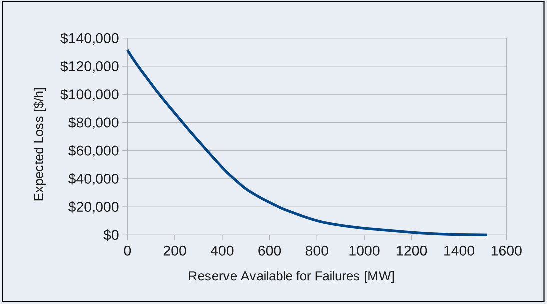


Rolling Evaluation: Expected Loss Cost Function for Reserve

- Evaluation: after realizing wind, treat reserve as soft constraint – derive a cost function to penalize for keeping too little reserve
- Besides wind, major uncertainty are failures (assume independent)
- Expected loss based cost, assuming generators fail every 1.5 years
- Planning: Stochastic models treat reserve as soft constraint



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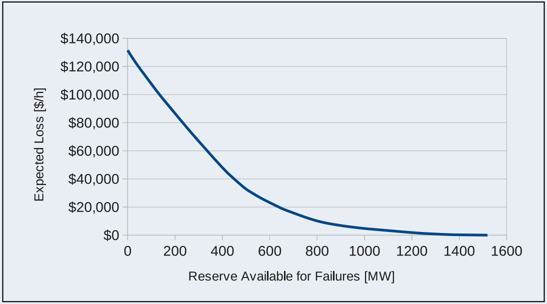

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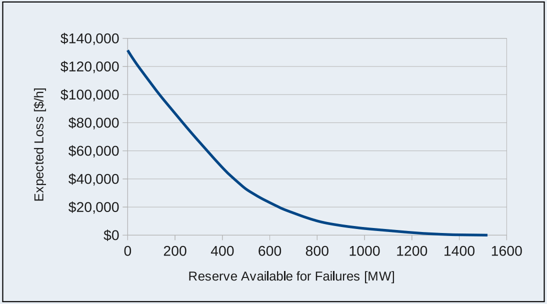

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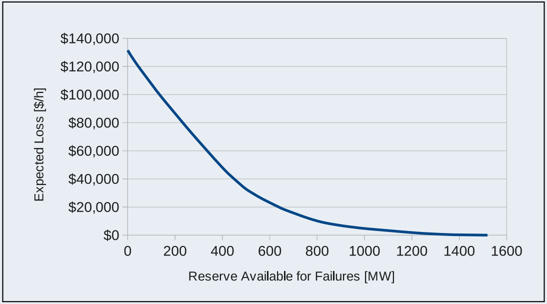

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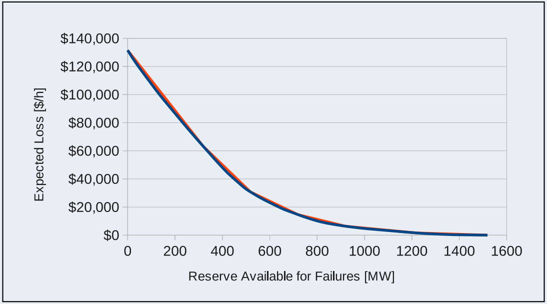
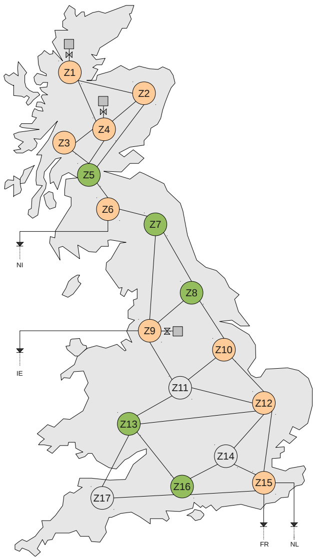


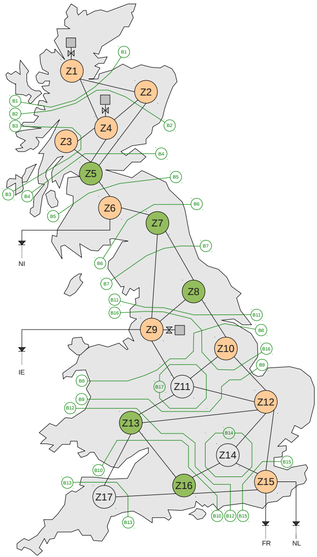
The British Model: Overview

- Centrally planned optimal social welfare model of the expected 2020 British National Grid
- Minimize fuel & carbon cost, using estimated generator efficiencies
- 130 conventional generators ≈ 64GW total capacity
- 160 wind farms ≈ 28GW total capacity (30% penetration)
- Pump storage: 2 Scotland, 2 Wales
- Interconnectors: Ireland, France, Netherlands



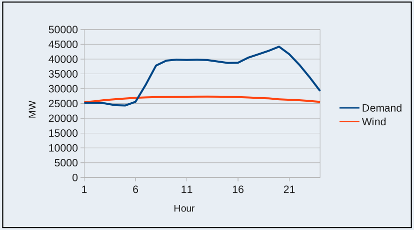
The British Model: Transmission

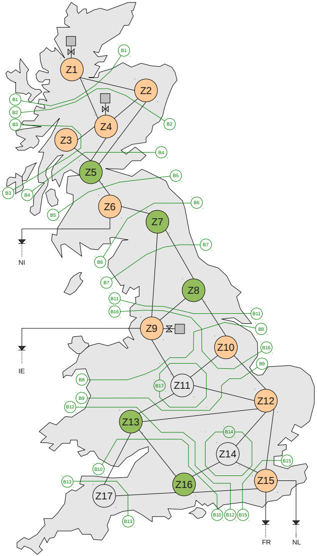
- 17 nodes, corresponding to National Grid study zones
- 27 transmission links, only real power variables, no losses, no phase angles
- transmission limits: single line and boundary import/export constraints
- local generation/demand, but global reserve with 47% min. conventional reserve



The British Model: LMPs & PS

- An example with very high wind
- Transmission limits split the system in price zones: north-south export pressure
- Pumped storage helps cope with the wind where possible





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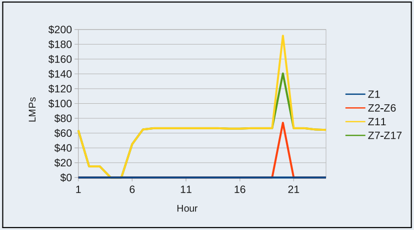

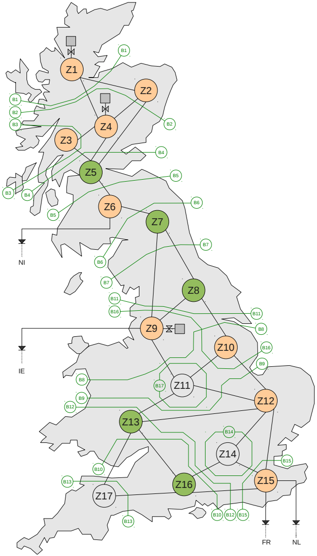

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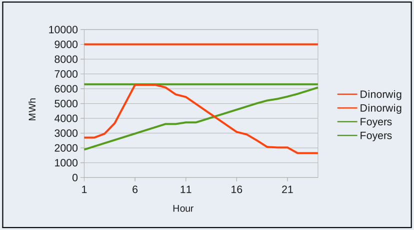
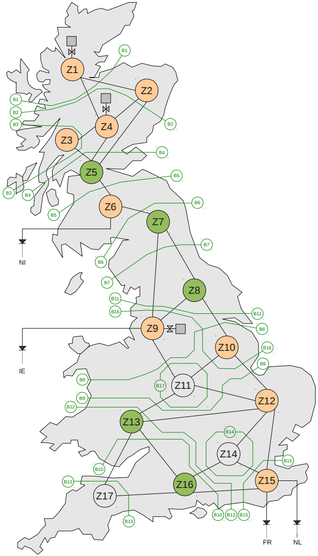
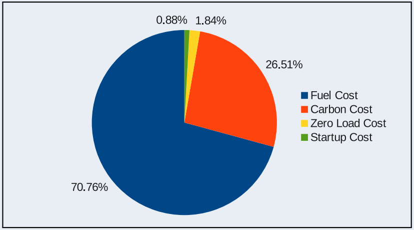
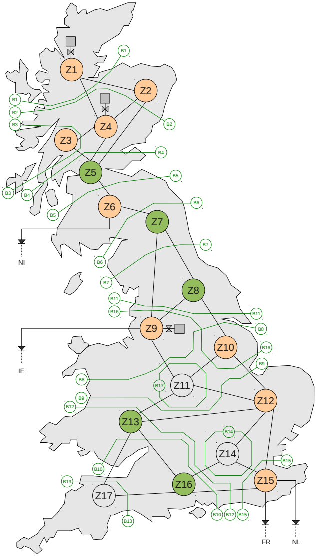




The British Model: Cost Drivers

- A breakdown of cost drivers
- Costs associated with binary decisions are small, thereby reducing the scope of optimization
- Besides good MIP cuts [5], this is a reason for small MIP gaps





Rolling Evaluation Results

- Focus of the study is performance of the different planning techniques in presence of wind forecast uncertainty
- One year long rolling horizon evaluation of deterministic and stochastic intraday and day-ahead models
- Utilized data: GB 2020 system, wind from 2010 (ARMA model fit to 2009 data), demand and HVDC profiles from 2013, but scaled to meet National Grid's expectations for 2020

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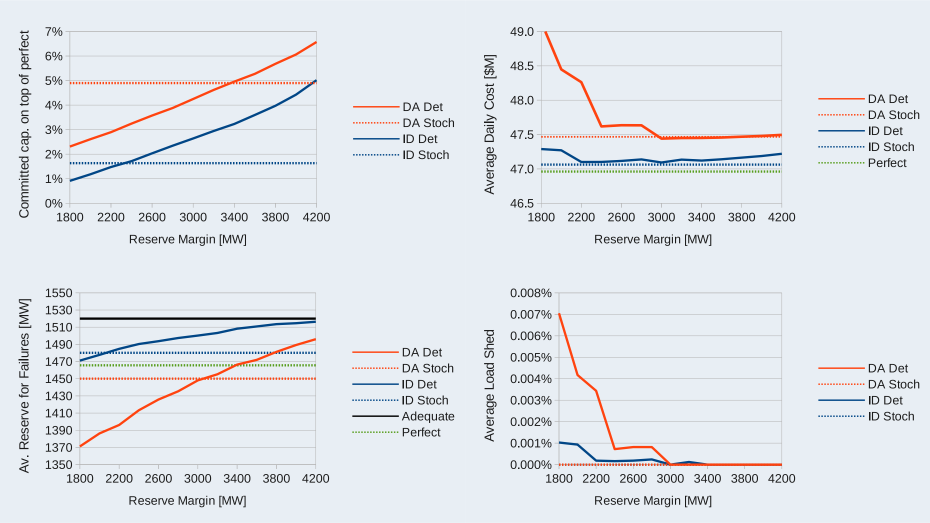
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Conclusions

- Intraday is superior to day-ahead, stochastic intraday models can respect startup notification times (0.9% $\approx$ \$0.5M daily)
- Intraday UC requires less spare capacity (lower forecast uncertainty)
- Stochastic models choose spare capacity levels close to "right" amount
- Stochastic models have better awareness of the location where spare capacity is required (transmission restrictions)
- Intraday: stochastic solutions are slightly more cost efficient than deterministic ones (between 0.5% and 0.05% $\approx$ \$230k and \$30k daily)
- Day-ahead: stoch. solutions are much better if det. models have too small reserve margin, but similar if they have large reserve margin (max. difference: 3.6 % $\approx$ \$2.7M daily)
- Figures to be interpreted in context: only 2.7% of total cost depend directly on binary decisions, remaining scope of optimization depends on variance of generation cost. This variance may be higher in a market environment.

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- Stochastic models choose spare capacity levels close to "right" amount
- Stochastic models have better awareness of the location where spare capacity is required (transmission restrictions)
- Intraday: stochastic solutions are slightly more cost efficient than deterministic ones (between 0.5% and 0.05% $\approx$ \$230k and \$30k daily)
- Day-ahead: stoch. solutions are much better if det. models have too small reserve margin, but similar if they have large reserve margin (max. difference: 3.6 % $\approx$ \$2.7M daily)
- Figures to be interpreted in context: only 2.7% of total cost depend directly on binary decisions, remaining scope of optimization depends on variance of generation cost. This variance may be higher in a market environment.

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Stochastic Models for Generation Unit Commitment

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School of Mathematics

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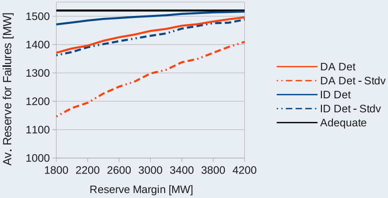
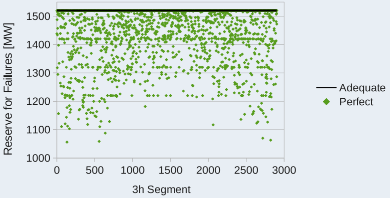
Backup: More Rolling Evaluation Results

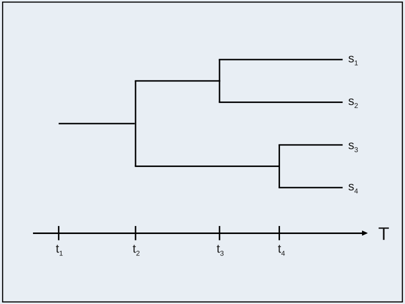
- Variability of reserve levels in the evaluation step
- Left: average and standard deviation of reserve levels in evaluation of deterministic intraday and day-ahead planning
- Right: even perfect foresight plan uses the essential part of reserve (at associated cost). Not more than the essential 1.52GW is ever allocated (same in all other evaluations).





Backup: Dantzig-Wolfe Scenario Decomposition

- Multiple scenarios with different residual loads
- Non-anticipativity constraints bundle the commitments in different scenarios. Here: multi-stage stochastic model.
- How to exploit the structure imposed by bundles?



Tree with four wind power scenarios.

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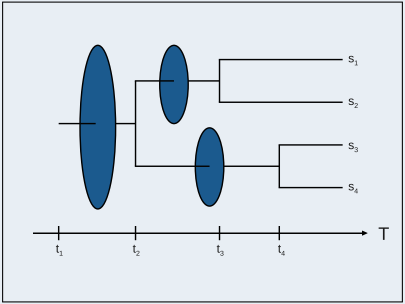

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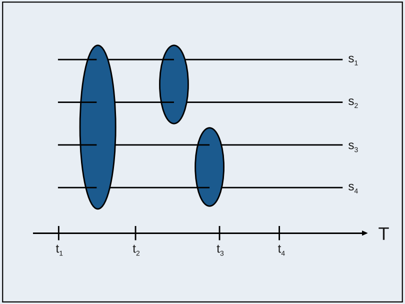

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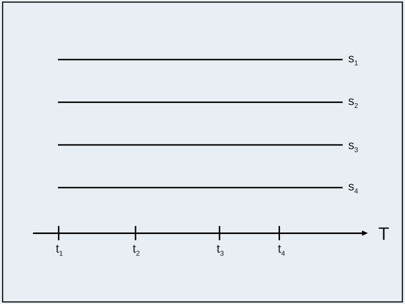
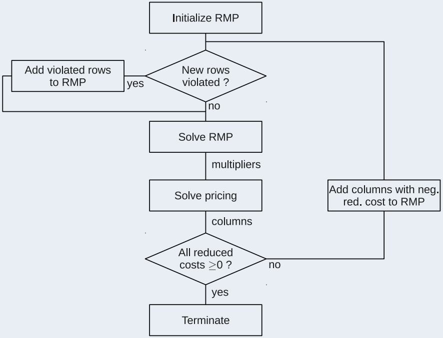


Four independent wind power scenarios.

Backup: Dantzig-Wolfe Scenario Decomposition

- An overview of the column generation procedure
- RMP initialization: initial primal and dual guess
- Dually stabilized: perturb RMP and initial LP relaxation
- Heuristics: RMP initialization, repeat in the process for better bounds



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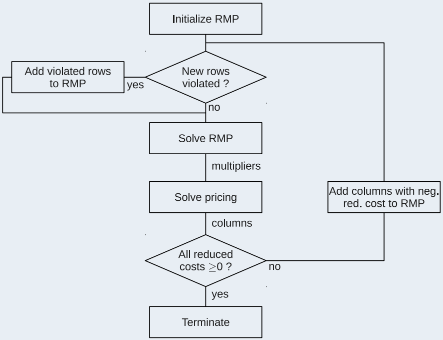

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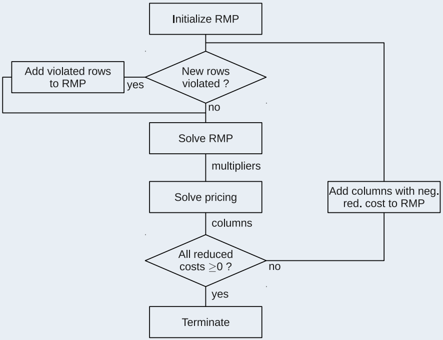

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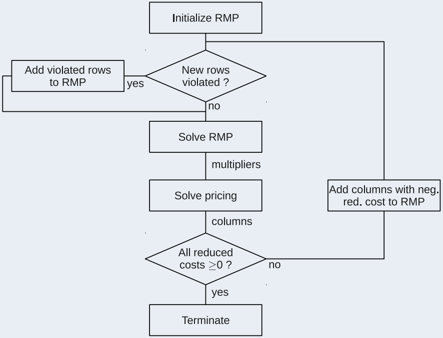

Backup: Dantzig-Wolfe Scenario Decomposition

- Performance results: B&C on det. equivalent vs. decomposition
- The decomposition outperforms direct B&C on large problems
- When opt. primal solution is found, MIP formulation is tight enough for CPLEX to terminate at root node (Heuristic+CPLEX)
- 16 threads, Linux 64bit 128GB RAM, Dual 8 Core Intel Xeon