Uncertainty in Energy Systems & Markets: Applications & Concepts

Kenneth Bruninx
“We aim to provide quantitative tools and results to support an efficient operation of, and transition towards, a low-carbon energy system.”
Energy Systems Integration & Modeling Group

- Currently 2 professors, 3 post-docs and 13 PhDs
- Focus areas:
## Modeling frameworks

- Operational model (UC – MILP)
  - Thermo-mechanical link
  - Unpredictability & variability
  - New technologies: e.g., CC(U)S, power-to-X, active grid elements, link to thermal systems in buildings
- Expansion planning models
  - Improve operational representation and technical detail
  - Uncertainty, adequacy, interconnections and market elements
- Optimization, equilibrium & agent-based modelling
- Open toolboxes and models (SPINE, ELDEST)

## Assessment of energy policy and market design

- Evaluation of EU ETS
- Interactions between RES support, possibly also ETS
- Impact of RES on electricity generation
- Flow-based market coupling, re-dispatch
- Cross-border balancing, sizing and procurement of reserves
- Distribution grid tariff design
- Role of storage (at different system levels, different services/markets, technologies)
- …
2 uncertainty in UC problems
Application: adequacy assessments

3 Chance-constrained programming
Applications: DR & PHES scheduling

4 Equilibrium modeling
Application: EU ETS & the Market Stability Reserve
Uncertainty in UC problems

- **Goal**: Endogenous probabilistic reserve sizing in a deterministic UC model, combining the simplicity of deterministic UC models & the cost-optimality of its stochastic equivalent.

- **Application**: The role of operating reserves in adequacy assessments

- **References**:
  - M. Hermans et al., *Analysis on the interaction between short-term operating reserves and adequacy*, Energy Policy, vol. 21, pp. 112-123, October 2018.
2 Uncertainty in UC problems

When should each power plant be started, stopped and how much should it generate to meet the demand for electric power at minimum cost?

Figure: Solar and wind power in the Belgian power system on June 5, 2014 [Elia].
Uncertain wind power forecast in a deterministic UC model

\[ p(W) \]

Demand or Wind power (MW)
Uncertain wind power forecast in a deterministic UC model

\[
\begin{align*}
\min & \quad C^{UC} + C^{ED} + C^{ENS} \\
\text{s.t.} & \quad D = G + W + ENS - CURT \\
& \quad D^+ = R^+ \\
& \quad D^- = R^- 
\end{align*}
\]

Not accounting for activation cost of reserves implies:

- **Reserve sizing**: exogenous trade-off between costs & benefits of flexibility (e.g., ENS vs. upward reserves).
- **Reserve procurement**: sub-optimal trade-off between technologies;
2 Uncertain wind power forecast in a stochastic UC model
SUC typically outperforms DUC, but requires dedicated decomposition techniques.

\[
\begin{align*}
\text{min} & \quad C^{UC} + \pi_\omega \cdot (C^{ED}_\omega + C^{ENS}_\omega) \\
\text{s.t.} & \quad D = G_\omega + W_\omega + ENS_\omega - CURT_\omega
\end{align*}
\]

Endogenous calculation of recourse cost allows

- **Optimal internal reserve sizing**: cost-optimal trade-off between flexibility and ENS/curtailment.
- **Reserve procurement**: cost-optimal trade-off between technologies/types providing flexibility.
Uncertain wind power forecast in a DUC-PR model

\[ D_5^+ \quad D_4^+ \quad D_3^+ \quad D_2^+ \quad D_1^+ \quad D_1^- \quad D_2^- \quad D_3^- \]

Probability (\( \cdot \))

Demand or Wind power (MW)

DUC-PR combines the speed & simplicity of a DUC model with the cost-optimality of an equivalent SUC problem.

\[
\begin{align*}
\min & \quad C^{UC} + C^{ED} + C^{ENS} + P_L \cdot C^{ACT}_L \\
\text{s.t.} & \quad D = G + W + ENS - CURT \\
& \quad D_L^+ = R_L^+ + ENS_L^+ + CURT_L^+ \\
& \quad D_L^- = R_L^- + CURT_L^- 
\end{align*}
\]

Endogenous approximation of reserve activation costs allows

- **Reserve sizing**: near-optimal trade-off between cost & benefits of flexibility.
- **Reserve procurement**: near-optimal trade-off between flexibility providers.

2 Case study & selected results

Case study

- Case-study on ~ Belgian power system (approx. 80 conventional power plants, 1 PHES);
- Assuming 30% wind energy penetration.

Selected results – illustrative example

1 Design of a DUC-PR method: number of reserve levels;
2 Internalizing the reserve sizing problem: trade-off cost reserve provision & ENS;
3 Optimal reserve allocation: trade-off expected deployment cost reserve providers.

Selected results – four week analysis

1 Expected operational cost, reliability, wind utilization for a specific week;
2 Computational cost.
Design of a DUC-PR model

Illustration: internalizing the reserve sizing problem

Illustration: cost-optimal reserve allocation

2 Expected operating costs & computational cost

E[operating costs] approximate those obtained from a stochastic equivalent at a fraction of the computational cost:

<table>
<thead>
<tr>
<th>W39</th>
<th>Spin.</th>
<th>Spin. &amp; non-spin.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SUC</td>
<td>DUC-PR</td>
</tr>
<tr>
<td>$E[TOC]$ (M€)</td>
<td>8.5</td>
<td>8.4</td>
</tr>
<tr>
<td>$E[TOC^*]$ (M€)</td>
<td>7.4</td>
<td>8.4</td>
</tr>
<tr>
<td>$E[WUF]$ (%)</td>
<td>96.4</td>
<td>93.8</td>
</tr>
<tr>
<td>$E[\phi]$ (MWh)</td>
<td>115.5</td>
<td>0.2</td>
</tr>
<tr>
<td>$E[WS]$ (%)</td>
<td>50.4</td>
<td>49.1</td>
</tr>
</tbody>
</table>

at a fraction of the computational cost:

<table>
<thead>
<tr>
<th>$P_{50}$ (s)</th>
<th>Spin.</th>
<th>Spin. &amp; non-spin.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SUC</td>
<td>DUC-PR</td>
</tr>
<tr>
<td></td>
<td>19,897</td>
<td>201</td>
</tr>
<tr>
<td>$P_{75}$ (s)</td>
<td>46,748</td>
<td>267</td>
</tr>
<tr>
<td>$P_{95}$ (s)</td>
<td>96,000</td>
<td>404</td>
</tr>
</tbody>
</table>

Analysis on the Interaction between Short-term Operating Reserves and Adequacy

Analysis on the Interaction between Short-term Operating Reserves and Adequacy

MINIMUM UPWARD FAST FLEXIBILITY NEEDS DURING PERIODS WITH SCARCITY RISK IN THE ‘CENTRAL’ SCENARIO [FIGURE 4-22]

Figure 4-22 represents the upward fast flexibility needs which are integrated as margins in the adequacy assessment. In practice, this means that part of the capacity of generation units and other capacity is reserved from the day-ahead market simulations, and kept available for balancing / flexibility purposes. This capacity has to dispose of fast flexibility characteristics (activation in 15 minutes).

Estimates based on DUC models may be overly conservative or represent an overvaluation of the VOLL.

<table>
<thead>
<tr>
<th></th>
<th>Probabilistic</th>
<th>Deterministic</th>
</tr>
</thead>
<tbody>
<tr>
<td>VOLL (€/MWh)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating reserve requirement</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>10 000</td>
<td>1 M</td>
</tr>
<tr>
<td>EENS based on UC simulations (MWh)</td>
<td>11.65</td>
<td>1.97</td>
</tr>
<tr>
<td>EENS based on 2000 dispatch evaluations (MWh)</td>
<td>14.6</td>
<td>2.43</td>
</tr>
<tr>
<td>EENS due to design reliability of reserves (MWh)</td>
<td>&lt; 0.01</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>LOLE based on UC simulations (h)</td>
<td>11</td>
<td>2</td>
</tr>
<tr>
<td>ELOLE based on 2000 dispatch evaluations (h)</td>
<td>0.273</td>
<td>0.032</td>
</tr>
<tr>
<td>LOLE range based on 2000 dispatch evaluations (h)</td>
<td>[0, 5]</td>
<td>[0, 2]</td>
</tr>
</tbody>
</table>

More accurate estimates obtained directly (without having to go through ED evaluations)

M. Hermans et al., Analysis on the interaction between short-term operating reserves and adequacy, Energy Policy, vol. 21, pp. 112-123, October 2018.
Implications of these assumptions (64 MCYs)
Conclusion

- Adequacy metrics obtained from DUC w. reserve constraints represent a worst-case situation
  - No contribution of (some categories of) operating reserves to the adequacy of the system
  - May over-/underestimate (real-time) adequacy metrics

- More accurate adequacy indices obtained from the DUC-PR model
  - By estimating the contribution of reserves to the adequacy of the system
  - Without increasing the computational burden or ex-post real-time MC dispatch
  - “Real-time” adequacy metrics may be a valuable addition to “day-ahead” metrics

- Impact of generation system flexibility on obtained results is small
3 Chance constrained programming in power systems

- **Goal**: Illustrating the use of chance constrained programming as a way to manage uncertainty

- **References**:
The system value of DR: arbitrage & operating reserve capacity

Min. $E[\text{Operating cost}]$

s.t. $D + D^H = G^C + G^R$

$D^+ = R^{C+} + D^{H+} + R^R + \phi$

$D^- = R^{C-} + D^{H-} + R^- + \chi$

$D^H = F(B, H, T, ...)$

$T \leq T \leq \overline{T}$

$D, D^H, G^C, G^R, R^{R+}, R^{R-}, \chi, \phi \in S$

A The system value of DR: arbitrage & operating reserve capacity

Min. \( E[\text{Operating cost}] \)

s.t. \( D + D^H = G^C + G^R \)

\( D^+ = R^{C+} + D^{H+} + R^R + \phi \)

\( D^- = R^{C-} + D^{H-} + R^- + \chi \)

\( D^H = F(B,H,T,...) \)

\( T \leq T \leq \bar{T} \)

\( D, D^H, G^C, G^R, R^{R+}, R^{R-}, \chi, \phi \in S \)

\( \Pr(D + D^H \leq G^C + G^R) \geq 1 - \epsilon \)

\( \Pr(D^+ \leq R^{C+} + D^{H+} + R^R + \phi) \geq 1 - \epsilon \)

\( \Pr(D^- \leq R^{C-} + D^{H-} + R^- + \chi) \geq 1 - \epsilon \)
The system value of DR: arbitrage & operating reserve capacity

Risk-neutral

Risk-averse

Perfect control

No DR

Poorer controllability
How can an aggregator valorize the flexibility of DR consumers with TCLs in uncertain energy markets, considering their limited controllability & guaranteeing thermal comfort?

Stackelberg Game
Scenario-based representation uncertain market outcomes

Set of solutions of the Stackelberg game between consumers and aggregator – if it exist – is enclosed in the set of solutions to the Nash Bargaining Game → Single agent participating in market!
Limitedly controllable DR providers force risk-averse aggregators to procure more energy in day-ahead markets, which may need to be sold in intraday at lower prices, which in turn lowers the aggregator’s profit.
The aggregator perspective

Limitedly controllable DR providers require the aggregator to carefully select a near-optimal $\epsilon$-value.

Price mark-ups in intraday markets ($ID^*$) and less controllable DR resources (higher $\sigma$) reduce benefit of the consumer-aggregator collaboration, especially at sub-optimal $\epsilon$-values.

### Poorer controllability

<table>
<thead>
<tr>
<th>Day</th>
<th>$\epsilon$ →</th>
<th>$\sigma = 0.05$ &amp; $\sigma^{NP} = 50$ MW</th>
<th>$\sigma = 0.1$ &amp; $\sigma^{NP} = 100$ MW</th>
<th>$\sigma = 0.15$ &amp; $\sigma^{NP} = 150$ MW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.5</td>
<td>0.4</td>
<td>0.3</td>
<td>0.2</td>
</tr>
<tr>
<td>$B$ (M€)</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td>$B^*$ (M€)</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>DA (M€)</td>
<td>0.98</td>
<td>0.89</td>
<td>0.79</td>
<td>0.66</td>
</tr>
<tr>
<td>ID (M€)</td>
<td>-0.004</td>
<td>0.09</td>
<td>0.19</td>
<td>0.31</td>
</tr>
<tr>
<td>ID* (M€)</td>
<td>-0.03</td>
<td>0.07</td>
<td>0.17</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>92 (25%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$B$ (M€)</td>
<td>1.62</td>
<td>1.67</td>
<td>1.62</td>
<td>1.59</td>
</tr>
<tr>
<td>$B^*$ (M€)</td>
<td>1.60</td>
<td>1.65</td>
<td>1.59</td>
<td>1.55</td>
</tr>
<tr>
<td>DA (M€)</td>
<td>1.66</td>
<td>1.62</td>
<td>1.48</td>
<td>1.38</td>
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<tr>
<td>ID (M€)</td>
<td>-0.04</td>
<td>0.05</td>
<td>0.14</td>
<td>0.24</td>
</tr>
<tr>
<td>ID* (M€)</td>
<td>-0.06</td>
<td>0.03</td>
<td>0.12</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>316 (50%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$B$ (M€)</td>
<td>0.13</td>
<td>0.15</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>$B^*$ (M€)</td>
<td>0.12</td>
<td>0.14</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>DA (M€)</td>
<td>0.22</td>
<td>0.20</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>ID (M€)</td>
<td>-0.09</td>
<td>-0.06</td>
<td>-0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td>ID* (M€)</td>
<td>-0.10</td>
<td>-0.06</td>
<td>-0.03</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Colder weather
Underground pumped hydro energy storage?

- Underground cavity used as lower reservoir
- Re-use existing caverns, old mines, quarries: significant investment cost reduction
- Challenge: uncertainty on geometry and hydraulic properties of lower reservoir, hence, uncertainty on net head available
C The day-ahead scheduling problem of a (U)PHES owner

• “Max. profit by participating in day-ahead energy & reserve capacity markets while respecting electromechanical & hydraulic constraints of the system”

• Challenging optimization problem:
  • Discontinous \textit{(forbidden operating zones)}
  • Non-linear \textit{(relation head – power)}
  • Non-convex \textit{(binary variables pump/turbine)}
  • Uncertainty on the available resource
The day-ahead scheduling problem of a UPHES owner

- “Max. profit by participating in day-ahead energy & reserve capacity markets while respecting electromechanical & hydraulic constraints of the system”

- Challenging optimization problem:
  - Discontinuous (forbidden operating zones) → binary variables
  - Non-linear (relation head – power) → piecewise linear approximation
  - Non-convex (binary variables pump/turbine) → binary variables
  - Uncertainty on the available resource Feasibility of the solution → chance constraints
C Summarized problem formulation

\[
\begin{align*}
\text{Profit from reserve markets} & \quad \text{Profit from energy market} & \quad \text{Operating cost} \\
\text{Max.} \sum_r 24 \cdot \lambda_r^{\text{res}} \cdot \left( \text{res}_{h,t,r}^T + \text{res}_{h,t,p}^P \right) + \sum_t \sum_\omega \pi_\omega \cdot \lambda_{t,\omega}^{DA} \cdot \sum_h \left( p_{h,t}^T - p_{h,t}^P \right) - C^{\text{op}}(p_{h,t}^T, p_{h,t}^P) \\
\text{s.t.} & \quad p_{h,t}^T, p_{h,t}^P, \text{res}_{h,t,r}^T, \text{res}_{h,t,r}^P \rightarrow q_{h,t}^P, q_{h,t}^T \rightarrow v_{h,t}^{\text{up}}, v_{h,t}^{\text{low}} \rightarrow h_{h,t}^{\text{net}} \\
& \quad p_{h,t}^T, p_{h,t}^P, \text{res}_{h,t,r}^T, \text{res}_{h,t,r}^P, q_{h,t}^P, q_{h,t}^T, v_{h,t}^{\text{up}}, v_{h,t}^{\text{low}}, h_{h,t}^{\text{net}} \in \chi \\
& \quad f_h^{\text{UPC,P}}(q_{h,t}^P, h_{h,t}^{\text{net}}) \leq p_{h,t}^P \leq f_h^{\text{UPC,P}}(q_{h,t}^P, h_{h,t}^{\text{net}}) \\
& \quad f_h^{\text{UPC,T}}(q_{h,t}^T, h_{h,t}^{\text{net}}) \leq p_{h,t}^T \leq f_h^{\text{UPC,T}}(q_{h,t}^T, h_{h,t}^{\text{net}}) \\
& \quad \text{Logical relationships (linear, binaries)} \\
& \quad \text{Feasibility space (linear)} \\
& \quad \text{Unit performance curves: piecewise linear approximation} \\
& \quad \text{Uncertain net head (availability of the resource)}
\end{align*}
\]
Uncertainty on (i) geometry and hydraulic properties of the underground reservoir and (ii) inaccuracies due to approximation of non-linear curves translate into uncertainty on the net head.
### Balancing profits & risk

<table>
<thead>
<tr>
<th>Risk $\varepsilon$</th>
<th>Day-ahead optimization</th>
<th>Out-of-sample results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expected Profit [€]</td>
<td>Computation Time [s]</td>
</tr>
<tr>
<td>0.5</td>
<td>2141.2</td>
<td>96</td>
</tr>
<tr>
<td>0.3</td>
<td>2075.0</td>
<td>62</td>
</tr>
<tr>
<td>0.1</td>
<td>1953.9</td>
<td>107</td>
</tr>
<tr>
<td>0.01</td>
<td>1891.5</td>
<td>32</td>
</tr>
<tr>
<td>0.001</td>
<td>1877.5</td>
<td>14</td>
</tr>
</tbody>
</table>

- **Out-of-sample analysis**: reserve activation, UPHES net-head & non-linear performance curves
- **Piecewise linear approximation** exploits flexibility more aggressively: higher profits at optimal risk-setting ($\varepsilon \approx 0.1$), infeasible schedules and high penalties when risk-neutral ($\varepsilon = 0.5$)
- **Strongly risk-averse** ($\varepsilon \rightarrow 0$) UPHES owners see less variation in profits, lower average performance and do not offer reserve capacity
Chance constrained programming is a versatile tool to represent decision making problems under uncertainty, wide range of applications in power systems.

Two distinct perspectives on demand response, which illustrate significant value in DR with TCLs, without impacting the thermal comfort of end-consumers. Impact chance constraints & limited controllability depends on perspective:
- Aggregator: liquid ID markets dampens impact
- System: absence of alternative recourse actions amplifies impact

Chance constraints allows hedging against infeasible operating schedules of UPHES (approximation errors, uncertainty on available resource), which can be recasted as SOC, hence, computationally efficient.

May be combined with scenario-based stochastic programming to represent exogenous uncertainties (e.g., market outcomes).
EU ETS

- **Goal:** Study the long-term impact of the recent changes in the EU ETS on evolutions in the power sector.

- **References:**
  - See website for latest versions.
From 5 €/ton CO₂ to 25 €/ton CO₂

Adoption MSR w. cancellation & increase LRF post 2020

Adoption MSR w/o cancellation
### EU ETS & Market Stability Reserve? (cont.)

<table>
<thead>
<tr>
<th>Year</th>
<th>Supply (MtCO₂)</th>
<th>LRF</th>
<th>Intake rate</th>
<th>Output rate</th>
<th>Limit (MtCO₂)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>if TNAC₂₀₁₇,₁₂ &gt; 833</td>
<td>if TNAC₂₀₁₇,₁₂ &lt; 400</td>
<td></td>
</tr>
<tr>
<td>2017</td>
<td>1,764 + 1,694</td>
<td>38.26</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2018</td>
<td>1,893</td>
<td>38.26</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2019</td>
<td>1,855</td>
<td>38.26</td>
<td>0.16 · TNAC₂₀₁₇,₁₂ + 0.08 · TNAC₂₀₁₈,₁₂ + 900</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>2020</td>
<td>1,816</td>
<td>38.26</td>
<td>0.16 · TNAC₂₀₁₈,₁₂ + 0.08 · TNAC₂₀₁₉,₁₂</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>2021</td>
<td>1,728</td>
<td>48.38</td>
<td>0.16 · TNAC₂₀₁₉,₁₂ + 0.08 · TNAC₂₀₂₀,₁₂ + 700</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>2022</td>
<td>1,679</td>
<td>48.38</td>
<td>0.16 · TNAC₂₀₂₀,₁₂ + 0.08 · TNAC₂₀₂₁,₁₂</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>2023</td>
<td>1,631</td>
<td>48.38</td>
<td>0.16 · TNAC₂₀₂₁,₁₂ + 0.08 · TNAC₂₀₂₂,₁₂</td>
<td>200</td>
<td>0.57 · Ŝᵧ⁻¹</td>
</tr>
<tr>
<td>2024-2061</td>
<td>48.38</td>
<td></td>
<td>0.08 · TNAC₂₀₁₂⁻²,₁₂ + 0.04 · TNAC₂₀₁₁⁻¹,₁₂</td>
<td>100</td>
<td>0.57 · Ŝᵧ⁻¹</td>
</tr>
</tbody>
</table>

- Annually declining cap (Supply), driven by an increasing linear reduction factor (LRF)
- Market stability reserves absorbs excess allowances, based on total number of allowances in circulation (TNAC, metric for surplus of allowances in the system)
- Holdings of MSR is limited, hence, may lead to cancellation of allowances.
4 Power sector investment under EU ETS

- Investments 2017-2061 under different designs of the EU ETS
- Simple representation of industry through abatement cost curves
- Large-scale MCP, including discrete triggers for actions MSR
- Solved using price-search algorithm inspired by ADMM
MSR 2018 significantly increases emission allowance prices & reduces cumulative emissions.

Cumulative emissions: -21.3 GtCO₂ (-41%)

Emission allowance prices

Supply of allowances, emissions cap and emissions
MSR 2018 advances transition coal/lignite to natural gas and natural gas to RES.

Emissions in the power sector (PS) and energy-intensive industry

Fuel shares in the power sector
4 What if…

- Five policy scenarios:

<table>
<thead>
<tr>
<th>Policy scenario</th>
<th>LRF</th>
<th>MSR 2019-2023</th>
<th>Cancellation</th>
<th>Power sector RES target</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSR2018</td>
<td>2.2%</td>
<td>24% - 200 MtCO₂</td>
<td>✓</td>
<td>34% (2020) - 32% (2030)</td>
</tr>
<tr>
<td>MSR2015</td>
<td>1.74%</td>
<td>12% - 100 MtCO₂</td>
<td>×</td>
<td>34% (2020)</td>
</tr>
<tr>
<td>MSR2018-LRF1.74</td>
<td>1.74%</td>
<td>21% - 200 MtCO₂</td>
<td>✓</td>
<td>34% (2020) - 32% (2030)</td>
</tr>
<tr>
<td>MSR2018-RES50</td>
<td>2.2%</td>
<td>24% - 200 MtCO₂</td>
<td>✓</td>
<td>34% (2020) - 50% (2030)</td>
</tr>
<tr>
<td>MSR2018-NC</td>
<td>2.2%</td>
<td>24% - 200 MtCO₂</td>
<td>×</td>
<td>34% (2020) - 32% (2030)</td>
</tr>
</tbody>
</table>

- Combined with 16 sets of assumptions on key parameters:
Impact MSR closely linked to increased LRF as a result of a feedback effect between cancellation volumes and the cost of meeting the cap in the future.
Higher EUA prices translate into higher EOM, hence lower REC prices;
Natural gas replaces coal, peaks around 2030 and is replaced by RES.
4 Conclusions

- Introduction of MSR & increase in LRF has significant impact on EUA prices and energy policy in general
- Example: equivalent LRFs for the period 2019-2061

- Revisions foreseen every 5 years, starting in 2021
Thank you for your attention! Questions?

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